



Distributed Wind Resource Assessment Framework: Functional Requirements and Metrics for Performance and Reliability Modeling

Heidi Tinnesand and Latha Sethuraman

National Renewable Energy Laboratory

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List of Abbreviations and Acronyms

DOE	U.S. Department of Energy
DWRA	Distributed Wind Resource Assessment
IEC	International Electrotechnical Commission
kW	kilowatt
NREL	National Renewable Energy Laboratory
NYSERDA	New York State Energy Research and Development Authority
REAP	Rural Energy for America Program
TI	turbulence intensity

Executive Summary

Over the past several years, various efforts have highlighted the variability in project performance and accuracy of performance prediction methods for distributed wind projects. These include:

- The 2016 and 2017 U.S. Department of Energy (DOE) distributed wind market reports, which show capacity factors for distributed wind turbine installations ranging from ~1% to 49%
- A total of 292 projects under the United States Department of Agriculture's Rural Energy for America Program (REAP), where an analysis of that data showed a 3-year average actual vs. predicted power production ranging from 62% to 134%, depending on project size. *Note: Because of the federal funding application process, REAP projects have more strict requirements than distributed wind projects in general.*

Improving the predictability and reliability of wind power generation will reduce costs by focusing investment to more lucrative installations and reducing investments with a low return due to poor performance. Developing tools to improve return on investments will reduce risk and naturally attract additional capital at lower financing rates into the distributed wind sector, a key cost reduction opportunity highlighted in the distributed wind future market assessment conducted by the National Renewable Energy Laboratory (NREL) (U.S. Department of Energy 2015).

To improve resource assessment predictions, we first need to evaluate the accuracy of current methods and understand the impact of specific input parameters and common assumptions made during the modeling process. A comprehensive, robust, and data-driven analysis of these inputs and their relative effectiveness at predicting performance will lead to improved models and best practices. As a result of the cost-prohibitive nature of commercial resource assessment tools, the distributed wind industry has developed independent tools. However, the distributed wind industry has historically lacked representative atmospheric and turbine performance data to validate and benchmark existing methodologies for predicting project performance and site suitability. There is also no industry-standardized methodology to document procedures, assumptions, or validation efforts.

Quantifying and refining the accuracy of project performance estimates would directly address several of the key challenges identified by industry stakeholders in 2015 as part of the distributed wind resource assessment (DWRA) workshop held by DOE/NREL. These efforts are also cross-cutting for several other facets of the distributed wind portfolio, including:

- Turbine reliability: better understanding of site turbulence and extreme winds
- Operations and maintenance costs: better understanding of general site characteristics
- Grid integration: better prediction of power output
- Site assessment: simpler, more accurate, and lower cost
- Cost of capital and perception of financial risk: higher accuracy of production estimates.

By generating a parameter framework and a functional loss and uncertainty approach, we will be able to highlight the impacts of various measurement or modeling approaches to operational performance. This could drive future R&D efforts that would have a large impact on achieving programmatic objectives, mainly improving consumer confidence and lowering the levelized cost of energy from distributed wind systems.

The focus of the DWRA performance framework presented in this report is to first clarify the key parameters that define the wind resource for any distributed wind turbine project and then describe the loss and uncertainty factors associated with long-term performance of wind turbine projects. Next it will identify and define the key parameters required to analyze the operational performance of a project. This framework could then be the foundation for understanding the predictability of the power and revenue from a project.

Wind project performance is defined in terms of the potential energy production as well as the uncertainty of the energy production estimate. Key parameters include:

- Wind resource
 - Wind speed
 - Wind shear
 - Turbulence intensity (TI)
 - Wind direction
 - Extreme wind parameters
 - Air density
 - Other resource factors (inflow/terrain, roughness, obstacles, and interannual variability).
- Wind project characteristics
 - Project configuration
 - Wind turbine specifications
 - Project costs.
- Wind project losses
- Energy production estimate uncertainty.

The first step toward validation of various models and approaches will be to obtain a better understanding of key input parameters related to distributed wind applications in resource assessment techniques. Quantifying the impact of different resource parameters and loss categories on performance will allow DWRA professionals to make choices about the degree to which parameters need to be measured and which models should be used to achieve an acceptable level of accuracy for the production estimate.

The next step is to characterize the key parameters that should be included in an operational performance data set to evaluate pre-construction energy estimates. These include:

- Turbine power
- Turbine status signals
- Wind resource parameters.

The sensitivity analysis was one step toward developing a clearer understanding of the priority and required accuracy for the identified parameters but will require further investigation to understand the ultimate impact on project economics. From the analysis it was clear that wind speed and direction are essential parameters for any performance estimate, followed by air density, veer, and turbulence intensity, particularly for small wind turbines. While density doesn't vary greatly on a particular site, the air density varies significantly across the United States, and developing a better understanding impact of density on the power performance of commercially available wind turbines will be highly valuable.

Near-term next steps in this research effort will likely include the following:

- Validating existing models to understand their limitations and appropriate uses
- Assessing current rules of thumb
- Combining the results of multiple research efforts to provide better industry-wide guidance on modeling methodologies and appropriate assumptions
- Improving and better documenting methodologies for assessment of interannual variability; understanding under which conditions the different methodologies are most applicable
- Performing additional sensitivity analysis on resource parameters
- Evaluating costs associated with various resource assessment methods
- Estimating uncertainty and financial impact of the various evaluation methods.

Following the completion of these activities, there should be an effort to support the distributed wind industry in assessing the accuracy and precision of existing or new performance assessment tools. Select approaches for conducting these assessments are being discussed.

Table of Contents

1	Overview	1
1.1	Objectives and Priorities	2
1.2	Scope	3
1.3	Summary of Wind Resource Assessment Approaches	3
2	Wind Project Performance Estimation	7
2.1	Wind Resource	9
2.1.1	Wind Speed	10
2.1.2	Wind Shear	10
2.1.3	Turbulence Intensity	11
2.1.4	Wind Direction	11
2.1.5	Extreme Wind Parameters	12
2.1.6	Air Density	12
2.1.7	Ambient Temperature	13
2.1.8	Terrain Effects, Roughness, and Obstacles	13
2.1.9	Interannual Variability	14
2.2	Wind Project Characteristics	14
2.3	Loss Framework	15
2.4	Uncertainty Framework	16
3	Resource Assessment Tools, Models, and Methods	17
3.1	Current DWRA Approaches (Fields, Tinnesand, and Baring-Gould 2016)	17
3.1.1	Model-Based Approach	17
3.1.2	Measurement-Based Approach	18
4	Wind Project Performance Assessment	20
4.1	Assessment Parameters	21
4.1.1	Operational Measurements	21
4.1.2	Operational Loss Parameters	23
4.2	Recent Assessments	25
4.2.1	Commercial Wind Projects: Results from the DOE’s A2E Performance, Risk, and Uncertainty Framework	25
4.2.2	Distributed Wind Projects: REAP and NYSERDA Project Performance Results from the Distributed Wind Market Report	26
5	Sensitivity Analysis	28
5.1	Analytic Hierarchy Process	28
5.2	FAST Analysis	30
5.2.1	Approach	32
5.2.2	T-1 Results	36
5.2.3	T-2 through T-4 Results	40
6	Benchmark Datasets	41
7	Conclusions and Recommendations	42
	References	44
	Appendix	46

List of Figures

Figure 1. Process map for DWRA models.....	5
Figure 2. Project production probability	7
Figure 3. Recommended turbine exclusion zone	14
Figure 4. IEC 61400-15 energy loss framework.....	15
Figure 5. IEC 61400-15 energy uncertainty framework	16
Figure 6. Single sensitivity plots from distributed wind future market assessment.....	21
Figure 7. Range of typical project losses as a percent of gross production	23
Figure 8. Preliminary results from the Performance, Risk, and Uncertainty Framework project.....	25
Figure 9. REAP and NYSERDA results: operational turbine performance vs. pre-construction energy estimate	26
Figure 10. Resource and turbine input parameters presented for consideration	29
Figure 11. Contribution from top five resource assessment factors.....	30
Figure 12. Power performance curves for turbines T-1 through T-4.....	32
Figure 13. Sample histogram of mean elementary effects of all parameters on mean electric power.....	36
Figure 14. T-1 sensitivity to stability	37
Figure 15. Sensitivity rankings of mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3.....	38
Figure 16. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	39
Figure 17. T-2 sensitivity to stability	46
Figure 18. Sensitivity rankings for mean electric power to different wind parameters (1) Bin 1 (b) Bin 2 (c) Bin 3	48
Figure 19. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	49
Figure 20. T-3 sensitivity to stability	50
Figure 21. Sensitivity rankings for mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	52
Figure 22. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	53
Figure 23. T-4 sensitivity to stability	54
Figure 24. Sensitivity rankings for mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	56
Figure 25. Sensitivity rankings for standard deviation of electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3	56

List of Tables

Table 1. Impact of Key Parameters on Energy Estimate Based on Approach.....	6
Table 2. Project Volume for Each Turbine Class	26
Table 3. Turbine Input Parameters.....	29
Table 4. Resource Factors that Impact Turbine Location Wind Speed	29
Table 5. Resultant Contribution	30
Table 6. Basic Specifications for the Four Turbines Analyzed	31
Table 7. Parameter Definitions for T-1 for Sensitivity Analysis	35
Table 8. Sensitivity Ranking for T-1 Based on the Total Number of Appearances	36
Table 9. Sensitivity Rankings for Turbine T-2	46
Table 10. Parameter Definitions for Simulating T-2	47
Table 11. Sensitivity Rankings for Turbine T-3	50
Table 12. Parameter Definitions for Simulating T-3	51
Table 13. Sensitivity Rankings for Turbine T-4	54
Table 14. Parameter Definitions for Simulating T-4	55

1 Overview

The focus of the distributed wind resource assessment (DWRA) performance framework is to first clarify the key parameters that define the wind resource for any distributed wind turbine project and then describe the loss and uncertainty factors associated with long-term performance of wind turbine projects. This framework could then be the foundation for understanding the predictability of the power and revenue from a project.

Over the past several years, multiple efforts have highlighted the variability in project performance and accuracy of performance prediction methods for distributed wind projects. The 2016 and 2017 U.S. Department of Energy distributed wind market reports illustrate the wide range of capacity factors for an assortment of distributed wind turbines.

Recent investigation into state and national incentive program data for 292 projects has highlighted the significant performance variability for turbines across all sizes of distributed project installations. Most of the projects were funded through the Rural Energy for America Program (REAP) and New York State Energy Research and Development Authority (NYSERDA) programs in which applicants were required to work with a trained installer and use technology with proven performance, though not necessarily certified turbines (U.S. Department of Energy 2015). In general, the same cannot be said for most distributed projects nationwide. Details of the data are included in Section 4.2.

In addition to numerous other examples, including several case studies in the recent site assessment report (Olsen and Preus 2015), these data provide a compelling justification for investigating and validating resource assessment and performance prediction methodologies. These activities would also be in line with the findings of the 2015 wind resource assessment workshop and survey, which were summarized in a state of the industry report published by NREL in 2016 (Fields, Tinnesand, and Baring-Gould 2016). Through that work, industry stakeholders identified nine challenges that, if solved, would provide a high return on investment for the distributed wind industry. These challenges include:

- Limited access to public data
- Minimal data, methodologies, and guidelines available for resource and site assessment validation and benchmarking
- Lack of education and outreach opportunities for the DWRA industry
- Need for better ways to access and incorporate site data for distributed wind projects
- Complexity and cost of Measure-Correlate-Predict approaches result in a lack of multi-year resource information used in project assessments
- Lack of robust methods for scaling wind data to typically lower hub heights for distributed wind projects
- Absence of standardization in DWRA methods
- Minimal focus on turbine site suitability
- Instrumentation, measurement systems, and data processing are too costly for many distributed wind projects.

Quantifying and refining the accuracy of project performance estimates would directly address several of these challenges and be cross-cutting for several other facets of the distributed wind portfolio.

Improving the predictability and reliability of wind power generation and operations will reduce costs and potentially establish a framework to attract new capital to the distributed wind industry sector. This report is the first part of a research effort to investigate the impact that improved resource assessment and energy estimation for distributed wind can have on:

- Consumer confidence
- Cost of capital
- Cost of ownership and operations
- Perception of financial risk
- Levelized cost of energy.

In general, resources published expressly for the distributed wind industry are limited. Many of the ideas used today have been modified from the utility wind industry and adjusted to smaller turbines based on the experience of industry experts. This paper seeks to align common challenges between DWRA and utility-scale resource assessment in hopes that the knowledge transfer can be seamless, efficient, and tailored to distributed wind industry needs. While the wisdom of experienced wind practitioners is valuable, the lack of distributed wind industry-specific resources can hinder consistency, training, and long-term industry expansion. These challenges demonstrate the need to pursue more rigorous DWRA processes. Improved methods could result in having the ability to quantify the impacts of various parameters on the resultant energy production and turbine reliability.

As with any distributed wind analysis, the following discussion is complicated by the breadth of the industry, from small single-kilowatt turbines to multiple utility-scale turbines installed behind the meter. To address this diversity, this work will employ the same distributed wind size classes described in the Distributed Wind Market Demand Model (NREL) and wherever possible link the approach or discussion to the relevant turbine size. The four turbine classes from that work are:

- Residential: up to 20 kilowatts (kW)
- Commercial: greater than 20 kW to 100 kW
- Mid-size: greater than 100 kW to just under 1 megawatt
- Large: 1 megawatt and greater (in a distributed application).

Utility-scale will be used to refer to all non-distributed wind turbine projects.

1.1 Objectives and Priorities

The DWRA performance framework will benefit industry stakeholders in the following ways:

- Establish a common framework for identification and quantification of key resource assessment parameters for predicting project performance

- Identify key parameters that should be included in a benchmark dataset or model validation processes to evaluate the accuracy of any resource assessment toolset
- Illustrate the connection among resource assessment, operational performance, and financial frameworks.

1.2 Scope

At present there is no systematic method used by the industry to validate the results of resource assessments except when financial incentive fund managers require production information. In some cases, post-installation assessments are completed if there is a large discrepancy between power generation by the turbine and predicted values, but this is performed on a case-by-case basis with limited direct efforts to insure the accuracy of future assessments (Fields, Tinnesand, and Baring-Gould 2016).

There is also no industry-standardized methodology to document procedures, assumptions, or validation efforts. Generally, there is a strong correlation between the level of effort in conducting the resource assessments and the size of the project, with smaller (residential and commercial) projects requiring low-cost, more automated, or user-derived processes for at least initial project screening while larger projects (mid-size and large) can afford and require expanded efforts that would include on-site measurements (Fields, Tinnesand, and Baring-Gould 2016).

The DWRA performance framework is designed to facilitate the evaluation of wind resource assessment methodologies and wind project performance models that generate energy production estimates. As a next step, this framework could be used to link energy production estimates with financial models. For example, the solar photovoltaic industry has experienced massive growth in recent years, in part due to business and financial model innovations including shared solar systems (solar gardens or community solar), third-party ownership (leasing), solar-secured loans, securitization, and other financing mechanisms. There is no reason these models can't also be applied to the distributed wind market. However, a key component to the adoption of these models is certainty in the cash flows from solar projects; distributed wind projects would likely need to realize similar predictability (Lowder et al. 2015), which is not currently the case.

By generating a parameter framework and a functional loss and uncertainty approach, we will be able to highlight the impacts of various measurement or modeling approaches to operational performance. This could drive future R&D efforts that would have the largest impact for achieving programmatic objectives, mainly improving consumer confidence and lowering the levelized cost of energy from distributed wind systems. The DWRA performance framework proposed herein combined with further investigation into the impact of various factors on wind project performance will offer a foundation for quantifying performance and uncertainty and the resultant impact on project performance.

1.3 Summary of Wind Resource Assessment Approaches

Figure 1 summarizes the various wind resource assessment approaches to illustrate the progression of complexity when moving from one approach to the next and to identify steps for which there are common data references, tools, and processes. Looking at the range of approaches in this way, it is possible to see opportunities to adapt various steps to improve the

accuracy of the simple or complex model-based approaches, which in turn improves the accuracy for residential, commercial, and mid-size distributed wind turbine project assessments.

While there are clearly defined turbine sizes for residential, commercial, mid-size, and large distributed wind projects, the same cannot be said for wind resource assessment approaches. Smaller projects tend to use simpler approaches; however, numerous other factors drive this choice. Because of this, future analyses will focus on quantifying the accuracy and impact of each element of the approach such that the end user can make choices based on the precision desired.

Figure 1 is a high-level snapshot of industry approaches for DWRA. This reflects current understanding and will continue to be refined with industry feedback.

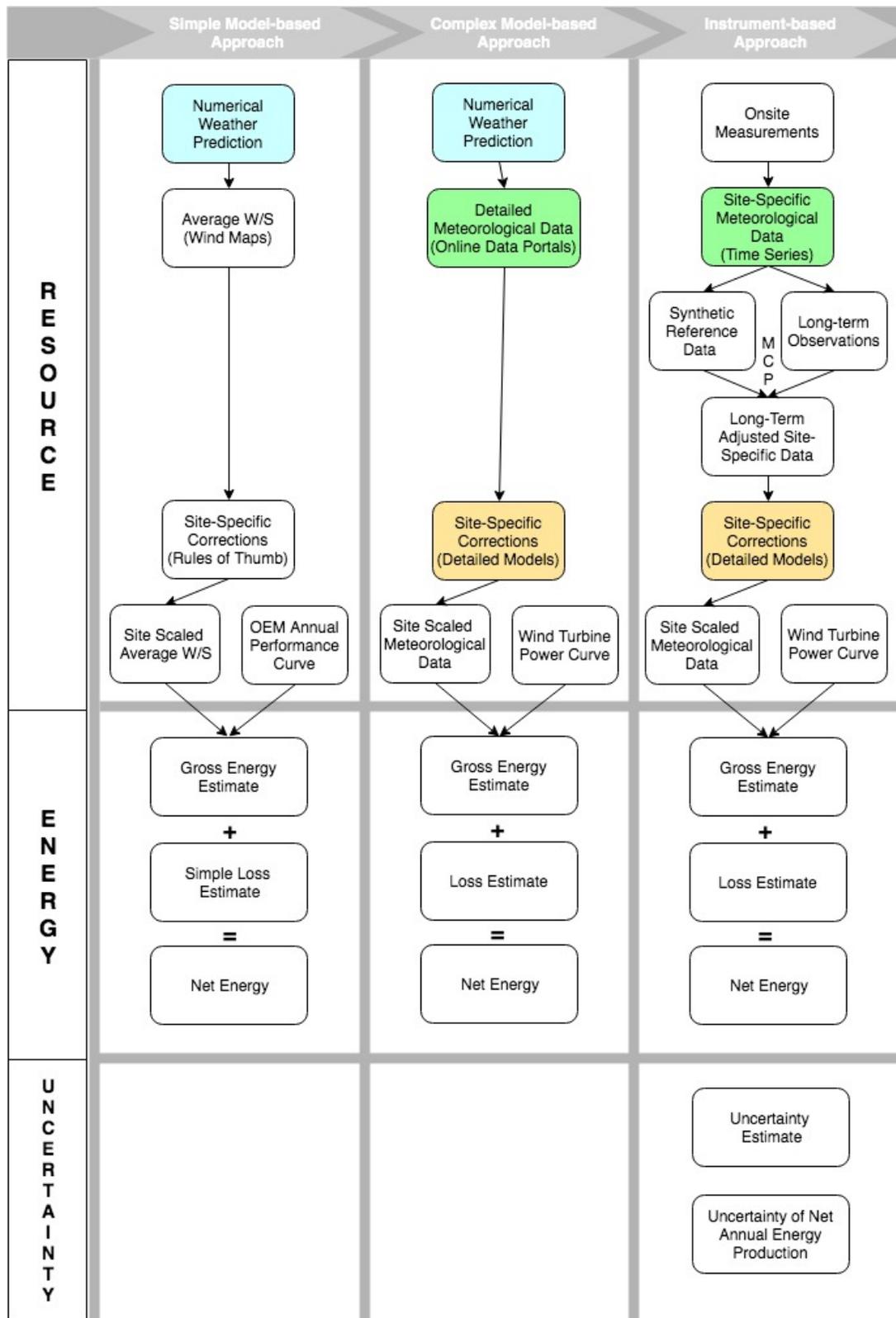


Figure 1. Process map for DWRA models

The number of parameters that could or should be considered for any wind project depends on a variety of factors but is primarily related to project or turbine size and requirements from various funding agencies or financial institutions. Of all the parameters described below, the most critical is wind speed as it has the largest impact on wind turbine power production. After wind speed, the priority of parameters becomes much more nuanced. Table 1 suggests a framework for identifying high-, medium-, and low-priority parameters to consider for various project sizes or approaches. The sensitivity analysis described in Section 5 is one step toward developing a robust decision-making framework for analyzing distributed wind project performance. Further investigation will be required to understand the precise impact of these parameters.

Table 1. Impact of Key Parameters on Energy Estimate Based on Approach

	Simple-Model (Residential, Commercial)	Complex-Model (Commercial, Mid- Size)	Instrument-Based (Mid-Size, Large)
Resource:			
Wind speed	High	High	High
Wind shear	High	High	Medium
Turbulence	Medium	Medium	High
Wind direction	High	High	High
Air density	Low	Low	High
Terrain effects	Medium	Medium	High
Roughness	Medium	Medium	High
Obstacles	High	High	High
Interannual variability	Medium	Medium	High
Losses:			
Availability	High	High	High
Wake effects	High	High	High
Electrical	Medium	Medium	High
Turbine performance	High	High	High
Curtailments and operational strategy	Low	Low	High
Environmental	High	High	High
Uncertainty:			
Plant performance	Project specific	Project specific	High
Vertical extrapolation	Project specific	Project specific	High
Spatial variation	Project specific	Project specific	High
Site measurement	Project specific	Project specific	High
Historic wind resource	Project specific	Project specific	High
Project lifetime variability	Project specific	Project specific	High
Other	Project specific	Project specific	Project specific

2 Wind Project Performance Estimation

Wind project performance is defined in terms of the potential energy production as well as the uncertainty of the energy production estimate. In other words, the wind project performance model represents the range of potential outcomes for energy production values, including the best-case and worst-case scenarios. Figure 2 illustrates the framework used by utility-scale developers to describe the potential range of outcomes for project stakeholders. The gross energy estimate is calculated from all the parameters detailed in Sections 2.1 and 2.2. Once this gross estimate has been calculated, the potential project losses are estimated using the International Electrotechnical Commission (IEC) 61400-15 loss framework described in Section 2.3. Finally, the range of outcomes or uncertainty for the net energy estimate is estimated using the IEC 61400-15 uncertainty framework described in Section 2.4. Once the result and likelihood of various outcomes are understood, an assessment of the risk for project owners or third-party investors can be initiated.

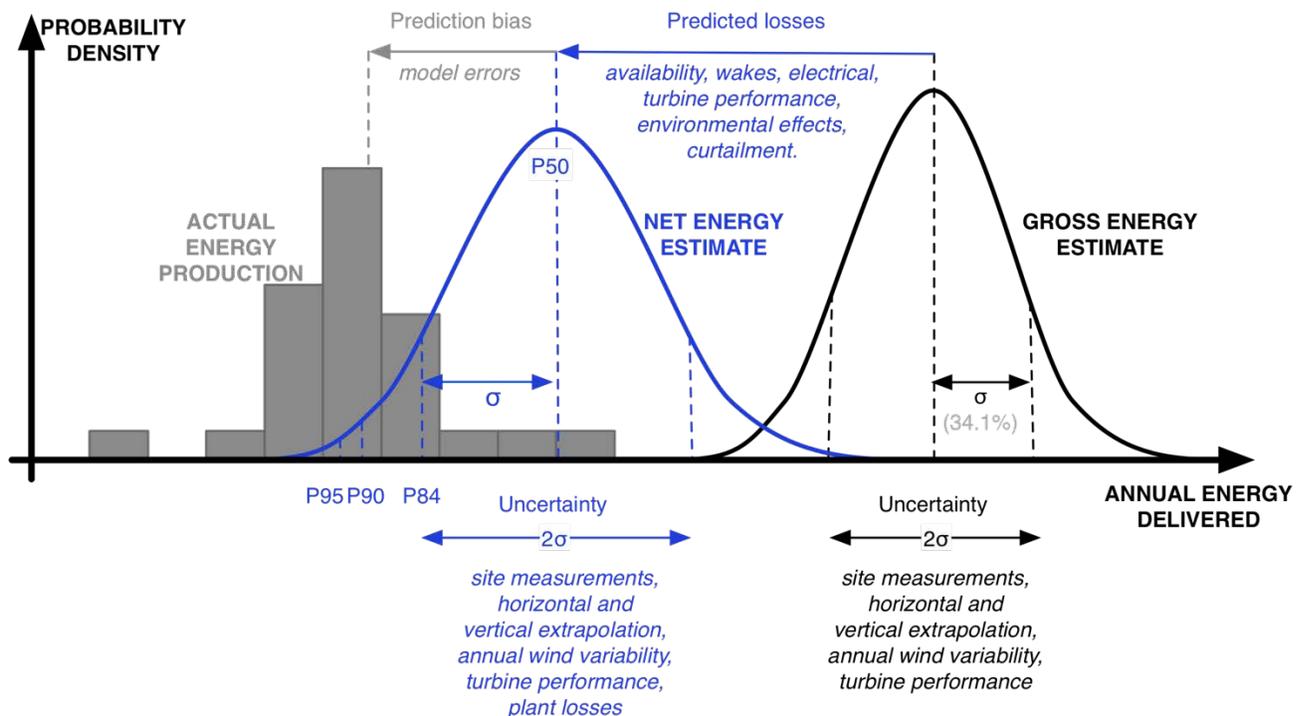


Figure 2. Project production probability

Therefore, to assess the range of outcomes, the following items must be accounted for:

- Wind resource (Section 2.1)
 - Wind speed
 - Wind shear
 - TI
 - Wind direction
 - Extreme wind parameters
 - Air density
 - Other resource factors.
- Wind project characteristics (Section 2.2)
 - Project configuration
 - Wind turbine specifications
 - Project costs.
- Wind project losses (Section 2.3)
- Energy production estimate uncertainty (Section 2.4).

The approach above allows representation of the wind project with relatively simple parameters and assumptions, mapping to all aspects of the wind project technology as well as the pre-construction and operational activities. For example, we can model the use of improved instrumentation or resource models by decreasing the uncertainty of onsite measurement data and models, spatial variation, etc. Alternately we can model the stakeholder impacts of improved models through improved loss assumptions as well as the uncertainty about estimates and losses. Although this approach was developed for the utility-scale wind industry, a simplified model could be established for the distributed wind industry as described in the following sections.

The temporal duration and resolution of energy production should match the required financial analysis needs. Financial institutions for distributed wind projects seldom impose requirements, but it is expected that as the industry evolves and new financing structures become available for projects, this will be increasingly important. In this scenario, wind projects will need to satisfy a variety of stakeholders, including the project owner, incentive program managers, financiers, and power offtakers. Each of these entities has a unique interest in projects and unique time horizons for investment, ranging from long-term averages to hourly. At this time, sub-hourly resolutions do not appear to be driven by stakeholder needs but may be included as sub-hourly aggregation can impact total wind project performance model accuracy. Therefore, the wind project performance model should be able to represent the average, median, and standard deviation wind project production on the following time scales:

- Multi-year: represents project lifetime production estimates
- One year: allows correlation to long-term data sets to adjust for intra-annual variability
- Monthly: illustrates season variability

- Daily: highlights seasonal variation and large-scale, weather-driven events
- Hourly: exposes diurnal variability
- Minutes: facilitates investigation of turbulence intensity at a particular location
- Seconds: enables assessment of wind turbine aerodynamic performance in relation to referenced power output assessments.

Many of these time scales are challenging to predict for a variety of reasons. It is therefore recommended that simple annualized methods should be considered as core requirements, but more detailed time series methods are a recommended evolution of the total modeling capability.

Most distributed wind projects use multi-year time scales exclusively. However, if financing requirements change or there is increased focus on turbine reliability and reduction of operations and maintenance costs, analysts may need to consider additional time scales.

The first step in understanding the financial impact of uncertainty in a measurement campaign—either in terms of project financing or payback in general—is to first understand the critical factors that affect turbine performance. This includes the wind resource and associated losses, which are introduced in the following sections.

2.1 Wind Resource

Understanding the wind resource at a proposed project location can be achieved in several ways, but the primary method is to directly measure the resource at the precise location(s) or to measure the resource at a nearby location and extrapolate that resource to the proposed project height and location(s). If the proposed project is a single turbine and the wind resource is measured at the proposed turbine location, then the basic measured parameters are sufficient to characterize the wind resource at that site, in the measured timescale. However, the measured data must be corrected to account for the long-term behavior of the wind resource at the site. If there are multiple turbines on a project, the wind resource is measured at a distance from the proposed turbine location, or the measurement duration is a year or less, the resource should be adjusted using the second set of parameters. For most parameters, there is a range of approaches, which loosely correspond to the three approaches summarized in Section 1.3. Each section begins with a description of the utility-scale approach, followed by the most common distributed wind approach, and ends with a summary of the range of approaches.

Parameters that can be directly measured or calculated from measurements include the following basic parameters:

- Wind speed
- Wind shear
- TI
- Wind direction
- Air density.

The following parameters are important to consider for adjusting measured or modeled wind resource in the temporal and spatial domains:

- Inflow angle/terrain effects
- Roughness
- Obstacles
- Interannual variability.

2.1.1 Wind Speed

Understanding the wind speed at a prospective turbine site is the most important factor to consider when deciding whether to install a wind turbine because the power produced changes with the cube of the wind speed.

The wind speed can be characterized in several ways, and the method chosen will impact the precision of the energy estimate. The most precise method for determining the site wind speed is to take measurements on site for a year or more and then correct the data using a long-term data source (see Section 2.1.9 for more information). Alternatively, the wind can be characterized using an annual frequency distribution—typically described by the Weibull distribution with a scale parameter “A” and a shape parameter “k.” The simple annual average wind speed for a typical meteorological year is the most basic method of characterizing the wind at a site. This is typically a value taken from a wind resource map and can be useful for larger projects when performing the initial site assessment to locate a good site within a region.

If on-site instruments are out of the question, it is best to use a site-specific wind distribution rather than the simple annual average because two sites with the same average wind speed but disparate distributions will have very different energy estimates. The discrepancy between the two values depends on the magnitude of the difference between the two distributions.

The two primary DWRA methods of characterizing the wind are to look at the simple average annual wind speed, typically used when estimating potential energy production at a residential site, or a frequency distribution, which is typically used on commercial or mid-size turbine projects. The simple annual average can only provide a general indication of the energy that could be produced and, as such, should be used with caution. To more fully understand the potential energy generation, it is important to understand the site-specific distribution of the wind speeds. This can be obtained through direct measurements of the site or through a variety of model-based approaches.

simple average → frequency distribution → time series data.

2.1.2 Wind Shear

Wind shear is the change in wind speed with height. Typically, the wind speed continues to increase as the distance increases above the ground, although this is not always the case. Wind shear is used in wind resource assessments when the wind speed is measured or estimated using a model at a height other than the hub height of the proposed turbine. In either of these cases, the wind shear profile is used to convert the wind speed to the height of interest. There are numerous choices to make regarding how to apply shear to the height of interest, as the value can vary by season, time of day, etc. The wind shear can be used to select the appropriate hub height for a given location to minimize the levelized cost of energy.

Shear is particularly important and challenging in the DWRA space as most distributed wind turbine deployments are sited in the lowest portions of the atmospheric surface layer. Additionally, high wind shear can introduce unbalanced loads on the rotor plane and thereby impact turbine reliability.

Typically, for distributed wind sites, the wind shear exponent, or in some cases a simple multiplication factor, is selected from reference tables that provide values based on the surrounding surface characteristics (i.e., forest or plains) and is often a single average shear value. A more complex approach uses an average shear value for each direction sector. There are a variety of sources for these tables with varying levels of validation. Some are derived from logarithmic wind profiles; others like the Wisconsin's Focus on Energy work are based on extensive empirical data (Wegley Orgill, and Drake 1980 and Olsen and Preus 2015).

Displacement height is another factor used exclusively in DWRA to adjust the effective distance from the ground to hub height when a turbine is sited near a forest. This parameter is a rule of thumb based on the forest density and is generally approximated at 67% to 75% of canopy height for deciduous to dense evergreen forests, respectively (Chiras 2010). This new height above the canopy is then used to apply the shear exponent to reach the turbine hub height.

single average based on site vegetation → average shear by wind direction sector based on site vegetation → measured shear at project location.

2.1.3 Turbulence Intensity

TI is the ratio of the wind speed standard deviation to the mean wind speed, measured over a period of 10 minutes. In general, the TI decreases with increasing wind speed. The TI at 15 m/s (IEC 2006) is typically used to determine the suitability of a turbine at a proposed wind site. TI impacts the energy produced by a wind turbine as well as the longevity of the turbine.

The impacts of TI on a small turbine's energy production are not particularly well documented, but there is evidence to support improved turbine performance in certain atmospheric turbulence conditions. Additionally, TI is a primary driver of fatigue loads for wind turbines. As such, it is critical to understand the relationship between turbine designs and site-specific TI; however, this relationship currently is not well quantified for most small wind turbines.

Generally speaking, the turbulence intensity at a prospective distributed wind project is estimated using the surrounding surface roughness and then adjusted up or down based on various tables or rules of thumb (Wegley, Orgill, and Drake 1980 and Olsen and Preus 2015) for nearby obstacles.

TI can reduce annual energy output anywhere from 15% to 25% because the small wind turbine power curves are typically measured at sites with lower TI than is seen at installed locations. TI is a major issue for small turbines because of their low height relative to surrounding obstacles and surface effects (Olsen and Preus 2015).

no TI → site average TI → TI for each operational wind speed.

2.1.4 Wind Direction

Understanding where the wind comes from throughout the year is important when siting a wind turbine; this knowledge allows the developer to avoid siting the turbine near obstacles or

obstructions that would reduce the wind speed coming from that direction or would induce wake or other losses. Understanding wind direction is also important because it is a major component in the calculation of the potential energy production on the site. For example, the wind may come from the north for most of the year, but the highest wind speeds come from the south for part of the year; this may mean that the most energy incident on the site is from the south, and the turbine should be sited accordingly.

A wind rose provides a more complete picture of the wind direction on site by graphically presenting the wind direction on a compass, with 12 to 16 sectors. The wind rose can represent pure wind direction frequency or combine the wind speed and wind direction parameters to construct a more complete picture of the wind resource. The latter two can be represented either as a percentage of time the various wind speeds blow in each direction sector or the percentage of the total energy that is generated from each direction sector. This is critical for properly evaluating a site.

If wind direction information is available for a distributed wind project, it is typically a single predominant direction sector rather than a wind rose, as described above. Not having access to all parameters can result in errors and uncertainty when planning distributed wind projects, especially for multi-turbine projects.

single dominant direction (simple average) → wind rose → time series data.

2.1.5 Extreme Wind Parameters

Within the IEC 61400-2 standard, which covers the engineering and safety of small turbines, extreme wind parameters are identified. These include extreme wind speed, extreme operating gust, extreme direction change, extreme coherent gust, and extreme coherent gust with direction change. These parameters are derived from onsite measurements or models that have the required data fidelity and are primarily important to consider in the context of turbine reliability. Certification loads modeling assumes specific maximum values for these parameters.

The 50-year extreme wind speed is generally considered to be the “survival” wind speed design limit for any wind turbine class. It is based on the reference wind speed, which is the extreme 10-minute average wind speed expected with a 50-year recurrence.

This parameter is seldom included in current DWRA and site assessment processes.

There is no progression of data complexity here. These parameters are only available with high-resolution time series wind speed data.

2.1.6 Air Density

Air density impacts the power production of a turbine; for utility-scale turbines, several power curves are available, based on the site’s average air density. The air density is calculated using measured temperature and pressure. Air density can also have significant implications for reliability. A turbine may be able to withstand higher winds if the air density is decreased.

Density-specific power curves aren’t typically available for non-utility-scale wind turbines, which can contribute to increased uncertainty in the energy estimate.

no air density → average site air density from nearby station → time series air density.

2.1.7 Ambient Temperature

In addition to being used in the calculated air density, temperature is one of the key measurements for understanding the amount of icing, or ice days, that a site will experience, which is a valuable input in the loss framework. However, other data are required to calculate an accurate estimate of icing days. This can be accomplished with humidity data or the ability to look at heated and unheated anemometer data.

Temperature is seldom included in current DWRA processes.

no temperature → average site temperature from nearby station → time series temperature.

2.1.8 Terrain Effects, Roughness, and Obstacles

Inflow angle, roughness, and obstacles near a proposed project location all have an impact on the wind flow, relative to the measured flow characteristics, if the wind flow isn't measured at the precise project location. Many of these effects are modeled for utility-scale projects using commercially available software.

Terrain effects include the contribution of the change in elevation in the near vicinity and the inflow immediately preceding the turbine in all directions. If the terrain is flat between the measured wind resource and the proposed turbine location and no other factors affect the wind flow (i.e., changes in roughness or obstacles), the measured wind resource can be extrapolated to the proposed turbine location. The accuracy of this approach decreases with increasing distance.

Surface roughness affects the wind speed near that surface. As the height above the surface increases, the wind speed increases. The rate at which the wind speed increases with height is a function of the roughness. A rough surface, such as a dense forest, will slow the wind just above the trees much more than wind flow just above a smooth surface, such as open water.

Obstacles impact the airflow by partially blocking or otherwise disturbing the flow. This disturbed flow is often referred to as wake. Waked flow reduces wind speed, affects wind direction, and increases turbulence.

In general, the effects from terrain, roughness, and obstacles are estimated in DWRA protocols, in part due to the prohibitive expense of the software packages described above and the lack of time series data to use as inputs. How these effects are estimated depends on a site assessor's experience with a particular area to make a judgment as to whether the area will be augmented or diminished from the modeled wind speed.

Estimates of the effect of surface roughness can be extracted from various tables, such as Tables 1 and 2 in the Siting Handbook for Small Wind (Wegley, Orgill, and Drake 1980).

For an obstacle that has a height of "H," the zone of disturbance is generally estimated to be 2H upwind of the obstacle, 20H downwind, and 2H tall, as shown in Figure 3. This rule of thumb for residential-scale turbines dates to studies from 1964 and 1979 (Van Eimern et al. 1964 and Frost and Nowak 1979).

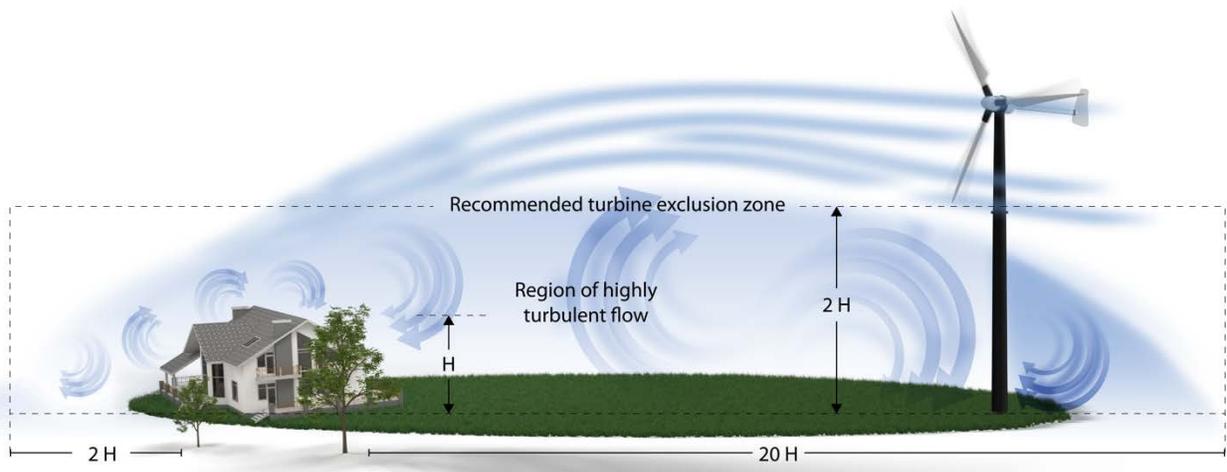


Figure 3. Recommended turbine exclusion zone

2.1.9 Interannual Variability

The wind resource varies from year to year, and depending on the timescale of the wind resource data, the measured data need to be corrected to a long-term reference data source to properly account for the variability of the resource over the project life. This variability can have significant implications to project viability and should be accounted for. A 2013 study by AWS Truepower indicated that interannual variability varies by location with values ranging from 3% to 10% across the globe, looking at three reanalysis datasets (Brower et al. 2013). It is therefore recommended to use interannual variability for the project area, rather than a standard rule of thumb. There are a variety of methods to place measured and modeled data into long-term historical context.

For the distributed wind industry, the discussion of interannual variability is complex. The wind maps or model-based approaches are based on wind speed averages for multiple years, so it is a long-term average of sorts; but for annual payback it's challenging to determine what the variability might look like year to year, which can have an impact on meeting production guarantees or various loan or lease payment scenarios. The nature of averaging also obscures visibility into the magnitude and frequency of extreme wind events, which can impact turbine reliability.

2.2 Wind Project Characteristics

Wind project performance models require basic wind project characteristics. These characteristics include:

- Project configuration (if there are multiple turbines, as in larger community-scale projects, or several large turbines installed behind the meter)
 - Rated capacity
 - Number of turbines
 - Geometric array.
- Wind turbine specifications
 - Rated capacity
 - Power curve
 - Hub height

- Rotor diameter
- Control parameters (e.g., high temperature shutdown).
- Project costs to estimate the levelized cost of energy if desired
 - Installed turbine cost
 - Balance of plant costs
 - Operations and maintenance costs.

The project configuration is a function of the project design; the wind turbine characteristics and project costs can be obtained from the turbine manufacturer or previous experience with purchase agreements and historical operations and maintenance costs.

Operations and maintenance costs are likely the largest unknown in the distributed wind industry, due to a lack of individual owners' previous experience to rely on.

2.3 Loss Framework

Wind project losses describe the physical drivers of the difference between gross energy production and net energy production. These can include effects such as electrical losses, wake losses, icing or blade soiling, and more. The wind project performance model should include a broad loss framework, which can account for a variety of technology improvements such as icing reduction approaches or improved models or instrumentation. In the absence of a distributed wind-specific loss framework, it is recommended to use and implement the IEC 61400-15 consensus loss framework, as shown in Figure 4.

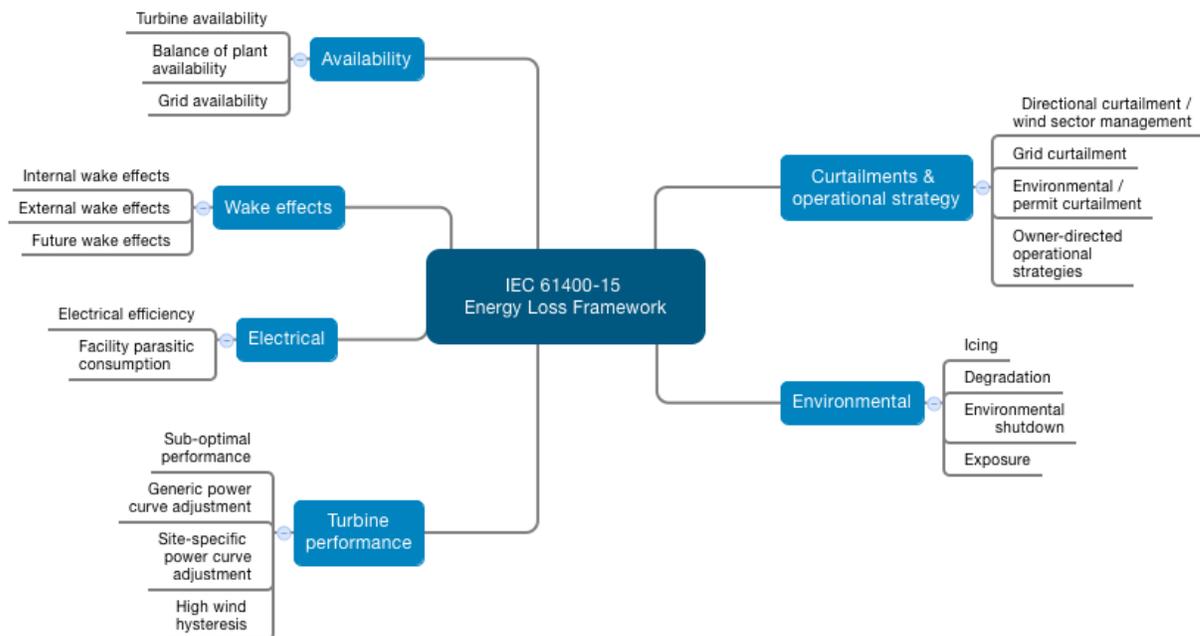


Figure 4. IEC 61400-15 energy loss framework

While most of the items in the loss framework will likely apply to any distributed wind project, a few may have a larger impact on the project performance than others for the distributed wind sector. The largest impact will likely result from:

- Turbine availability
- External wake effects
- Turbine performance (all categories)
- Environmental (all categories).

2.4 Uncertainty Framework

Wind project uncertainty quantification methods are used to describe the likelihood of potential outcomes for potential investors and other project stakeholders. The distribution of energy production outcomes is of interest as it can have dramatic impacts on cash flows, investment security, and profitability. The wind project uncertainty model should follow the current industry consensus that is the IEC 61400-15 uncertainty framework, as shown below in Figure 5. The model should also be able to combine uncertainties and perform Monte Carlo simulations for populating uncertainty distributions. However, this level of effort is beyond the scope of typical distributed wind industry projects.

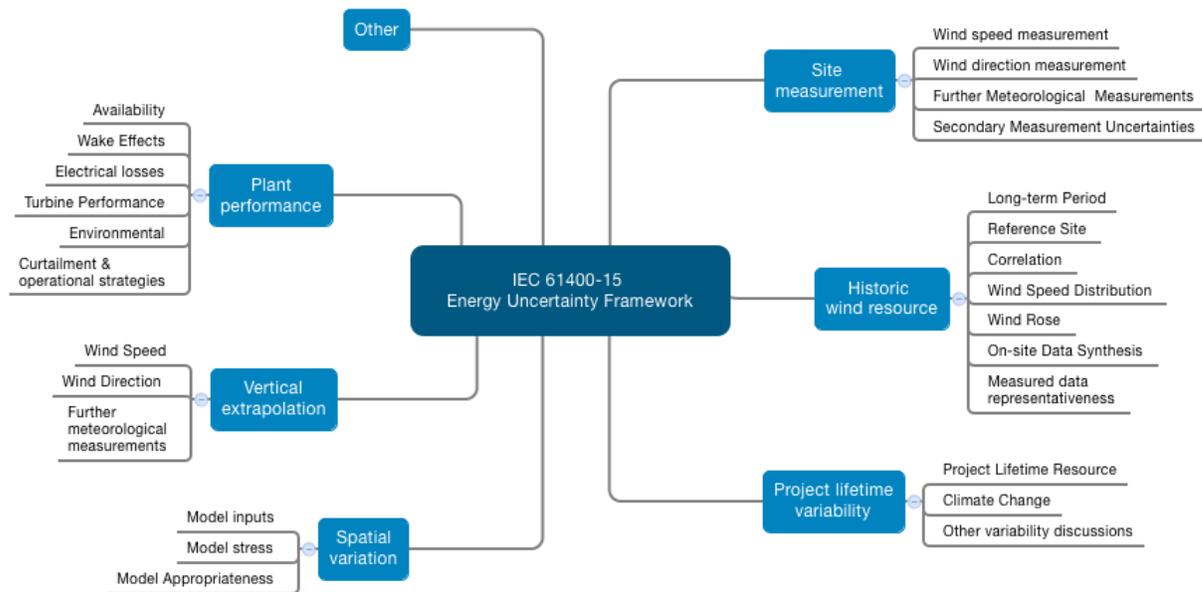


Figure 5. IEC 61400-15 energy uncertainty framework

Similar to the loss framework, all variables in the IEC 61400-15 Energy Uncertainty Framework are applicable to any distributed wind project to some degree, though the contribution from various factors will vary greatly depending on the models and other tools used, the source of wind input data, turbine type, how well the turbine was sited, and other factors.

3 Resource Assessment Tools, Models, and Methods

There are numerous commercial and open access wind plant production models available, such as OpenWind, WindFarmer, and WindPro. Most of these tools focus on wind project design and offer simple energy production, energy loss, and uncertainty models as part of the software package. While many of these commercial models have the capability to input and address the parameters described in Section 2, they often come with expensive licenses and little opportunity for customization, integration with other systems (e.g., systems engineering), or automation.

As a result of the cost-prohibitive nature of these commercial resource assessment tools, the distributed wind industry has developed independent tools. However, the industry lacks representative atmospheric and turbine performance data to validate and benchmark existing methodologies for predicting project performance and site suitability. New standard test cases and guidelines could include discussion of which tools, processes, and methodologies are appropriate for specific site conditions and the limitations of various approaches.

3.1 Current DWRA Approaches (Fields, Tinneland, and Baring-Gould 2016)

The DWRA workshop and survey in 2015 facilitated by DOE/NREL demonstrated that there are many approaches for conducting a wind resource assessment at a potential distributed wind site. These approaches vary by levels of complexity, cost, and company engagement; however, there are two basic categories of wind resource assessment that are commonly used in the distributed wind space: models and onsite measurements. The most common tools include wind maps, desktop spreadsheets, and desktop linear models. The following is a summary of the two principal approaches discussed during the DWRA workshop.

3.1.1 Model-Based Approach

A model-based approach uses pre-existing datasets such as wind maps or re-analysis¹ data as an input for an energy assessment. This input is then modified for a specific turbine location using scaling² models, expert judgment, or rules of thumb to determine the impacts of site-specific conditions such as terrain, roughness, and obstacles. This approach does not include onsite measurements but can include a site visit for site assessment refinement purposes. There is a large degree of variability in this approach, from the simple use of publicly available annual average wind speed estimates to detailed, site-specific physical modeling. This approach could also include the assessment of measured data from a nearby location to better understand local conditions.

¹ Re-analysis refers to a family of data products that describe the long-term state of the global atmosphere. These data products are often used to initialize site-specific wind resource models. Examples are MERRA, ERA-Interim, CFSR, and National Center for Environmental Protection/National Center for Atmospheric Research Reanalysis Project; see <https://reanalyses.org/> for more information.

² Scaling refers to the process in which measured or modeled data are adjusted using defined parameters to a different height above the ground. In simple terms, it is a process that uses the power law to adjust the reference height of data, typically downward to a lower altitude above ground for distributed wind applications; but in almost all cases, it is not a simple process. It should be noted that downscaling is typically used in the creation of all modeled data because numerical weather prediction models calculate wind speeds at very high altitudes. Downscaling methods and models are typically business sensitive and therefore difficult to compare.

The model-based approach is predicated on numerical weather prediction models for the major data input. Numerical weather prediction can be defined as reanalysis data (Modern Era Retrospective-Analysis for Research and Applications, ERA-Interim, and Climate Forecast System Reanalysis) or a finer-scale data product generated using the Weather Research & Forecasting Model. The data from the numerical weather prediction datasets are then used to create a static wind map or made available, typically for a fee, on a web-based portal. The outputs from these products are meteorological statistics such as annual average wind speed or wind speed and direction frequency distributions, temperature, and air density, respectively. These meteorological statistics are then corrected or scaled to the turbine height and location using a process called down-scaling that considers terrain, surface roughness, obstacles, and other local conditions. This down-scaling can be in the form of empirical rules of thumb or site-specific models such as Wind Atlas Analysis and Application Program or computational fluid dynamics. Finally, an energy prediction is formed using a wind turbine power curve or an annual energy production look-up table.

3.1.2 Measurement-Based Approach

On-site measurements can also be combined with other model or analytical tools (aspects of the first approach) to perform higher-resolution assessments, reducing the overall uncertainty of the energy and site condition estimate. The on-site measurements can include meteorological towers or remote sensing devices. In general, larger projects (typically mid-size or large turbines) tend to require on-site measurements to ensure that energy estimates are more accurate and likely to meet the projected energy output and therefore the economics of the selected turbine.

The measurement-based approach is recognized across the industry as being more accurate for predicting energy production as well as site suitability. Instruments are, however, more expensive and more time consuming than traditional model-based approaches, which has led to limited uptake in the distributed wind sector.

The measurement-based approach generates its own site-specific wind statistics and largely eliminates the need for site-specific corrections accounting for terrain, surface roughness, and obstacles. There is typically an additional step known as Measure-Correlate-Predict to adjust the relatively short-term measurements to a long-term representation of the wind statistics based on a modeled or other nearby, long-term reference wind measurement station. This long-term representation is then combined with the power curve to generate gross energy estimates, and these estimates are subsequently run through a loss and uncertainty estimation process to arrive at the net annual energy production and expected variability.

One of the least agreed-upon aspects of on-site measurements is when they should be used to measure the wind resource of a potential project. Opinions vary on the minimum size at which on-site measurements should be initiated, ranging from 50 kW to 750 kW, with outliers on both ends suggesting that on-site measurements are never realistic for distributed wind projects or are realistic only for projects greater than 750 kW. Increased site complexity is also a driver that leads to an expanded use of on-site measurement.

Additional topics during the discussion included the role of remote sensing versus tower-based measurements, and the minimum duration of on-site measurements required for the Measure-Correlate-Predict process to provide high-quality results. At present there is scarce analysis to guide a simplified Measure-Correlate-Predict process for the distributed wind industry, but this will become increasingly important as the industry grows and more distributed projects utilize mid-size and larger turbines.

4 Wind Project Performance Assessment

There are three primary steps for calculating and then evaluating preconstruction energy estimates vs. operational performance. The first step is to calculate the bulk results, defined as a percentage of metered production over predicted performance. This is the simplest step and will not consider any unusual operational conditions that may be outside of the performance frame. Next, if operational data exist for the project, the sources of variation can be explored and evaluated. This process will take more time and data sources to complete. Finally, there is an opportunity to approximate the maximum possible accuracy that could have been obtained for any project by eliminating extenuating issues and events that cannot reasonably be predicted, such as catastrophic failures/serial defects, natural disasters, or unusual curtailment.

To make a complete assessment of the operational performance of a wind project, one needs a robust measurement campaign for the turbine including power production, turbine status signals, and measurements for the wind resource, as described in Section 2.1. These operational parameters are described in Section 4.1.1. Details of the project characteristics and operational data related to the loss parameters estimated during the pre-construction evaluation will also need to be assessed. Without wind resource measurements and turbine status signals during operation, it is infeasible to evaluate the cause of any variation in performance from the preconstruction energy estimate.

Unless the causes of variation are understood, it is difficult to refine the models for estimating performance on prospective projects. Unexplained variation then leads to high levels of uncertainty in the preconstruction energy assessment, as detailed in the uncertainty framework in Section 2.4. Uncertainty leads to unpredictable power generation, which impacts consumer confidence, reliability of the revenue from the project, and the cost of ownership. Improving the predictability and reliability of wind power generation will reduce costs by focusing investment to more lucrative installations. Developing tools to improve return on investments will naturally attract capital into the distributed wind sector, a key cost reduction opportunity highlighted in the distributed wind future market assessment conducted by NREL (Lantz et al. 2016) and illustrated in Figure 6.

Understanding the sources of variation during operation can be challenging. The first step toward developing capability in this area is to ensure that each operating project has a robust data-monitoring platform. Implementing monitoring has a twofold benefit: not only does it improve the capacity to verify the preconstruction energy estimate but it also enables maintenance divisions to provide timely and cost-effective O&M services.

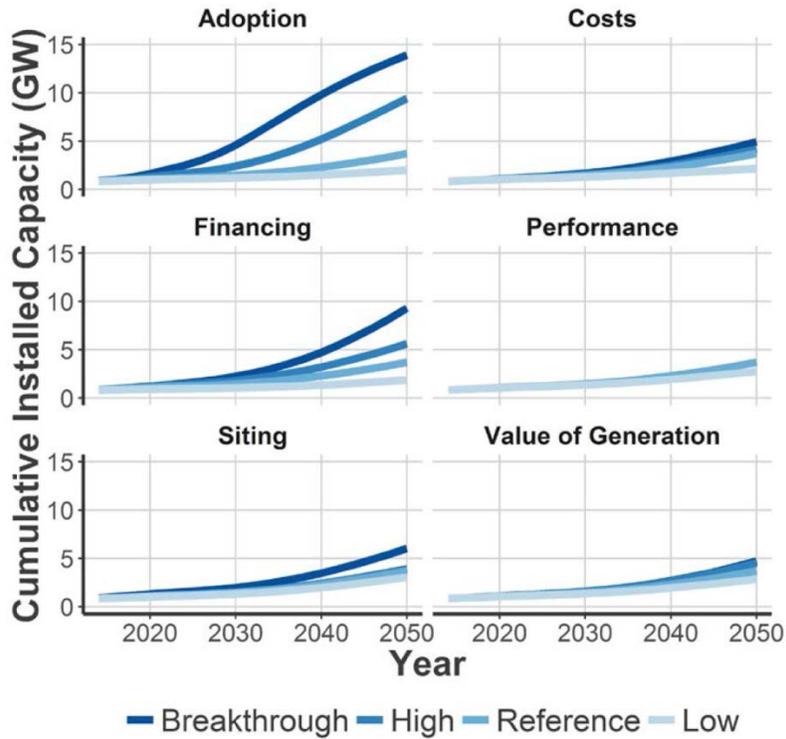


Figure 6. Single sensitivity plots from distributed wind future market assessment

4.1 Assessment Parameters

The following two sections describe the parameters required to evaluate the operational performance of a project and determine the causes of variation between the pre-construction energy assessment and actual performance.

4.1.1 Operational Measurements

A minimum of three parameters must be measured in order to evaluate operational performance of a project: turbine power, turbine status, and on-site wind resource.

4.1.1.1 Power

The only required parameter for calculating the predicted vs. actual performance of a turbine is the power output of the turbine. There are several ways to measure this data and various locations in the system where this measurement can be taken.

On a commercial wind farm, unless testing under a formal power performance measurement, the power is measured at or near individual turbines or at the point of metering for the entire site, which can encompass many turbines.

For single utility turbines, the power measurement can be taken in the turbine nacelle where the value is the maximum total power output from the turbine. The measurement can be read from the turbine's data acquisition system or measured independently by installing a secondary set of voltage taps, current transformers, and a watt transducer. Other common locations to measure power are at the base of the turbine or the power off-take location.

For small wind systems the power output from the turbine is typically measured at the residential electric panel.

Regardless of how many turbines are being evaluated or the size of the turbine under consideration, the key consideration is to ensure that the location of the measurement reflects the location for the initial evaluation, which would take into consideration items such as electrical line losses if measuring the power anywhere other than the nacelle.

4.1.1.2 Turbine Status Signals

Turbine status signals are critical to quantifying the amount of performance variation due to variables related to turbine operation such as curtailment or downtime. Signals can include turbine operational state, grid conditions, manual stops, or restrictions. Wind turbine operational state could include indications of states such as emergency, failure, stop, pause, warning or running. Curtailment is typically related to parameters outside of the turbine, such as utility or environmental regulations. Downtime captures all turbine maintenance, scheduled or unscheduled. Curtailment and downtime are both typically included in the preconstruction energy estimate but have high levels of uncertainty due to many factors.

Curtailment and downtime are challenging to quantify for utility-scale and small wind turbines due to the lack of dedicated signals. For utility-scale turbines, often more than one signal or channel can exist, which capture curtailment and downtime events. For small wind turbines monitoring systems are extremely limited; as such there is seldom a status signal.

4.1.1.3 Wind Resource

It is critical to measure the wind resource at an operational wind turbine site to capture the actual wind speeds and environmental conditions after the turbine is installed. Without this information, it is impossible to separate and calculate the impact on power production from the wind speed during the year apart from other factors such as the turbine performing different from the manufacturer's specification or the turbine having low availability (high downtime) due to unexpected faults and unscheduled maintenance.

There are two potential locations to measure wind speed near an operational wind turbine: a nacelle-mounted anemometer and an anemometer mounted on a nearby meteorological (met) mast. The wind speed from a met mast is typically more accurate than the measurement on top of a nacelle because it is in a position that is free of obstructions and is not impacted by the turbine's rotor.

For power performance measurement in the utility sector, the standard is to use a met mast upwind of the turbine in the primary measurement direction. According to the IEC standard (IEC 2005), if the terrain between the met mast and the turbine is complex, there will be a calibration between two met masts prior to testing. The turbine manufacturer uses a similar method when determining the relationship between the upwind free stream wind speed and the wind seen by the nacelle-mounted anemometer.

For the typical distributed wind turbines, there are no wind speed measurements available.

4.1.2 Operational Loss Parameters

Project losses during operation include those areas identified in the Energy Loss Framework in Section 2.3—this covers availability, wake, suboptimal turbine performance, curtailment, etc.—and are described in more detail below. In general, project losses are difficult to measure and therefore quantify, but Figure 7 gives a range of typical losses for commercial utility-scale projects based on a review of published literature.

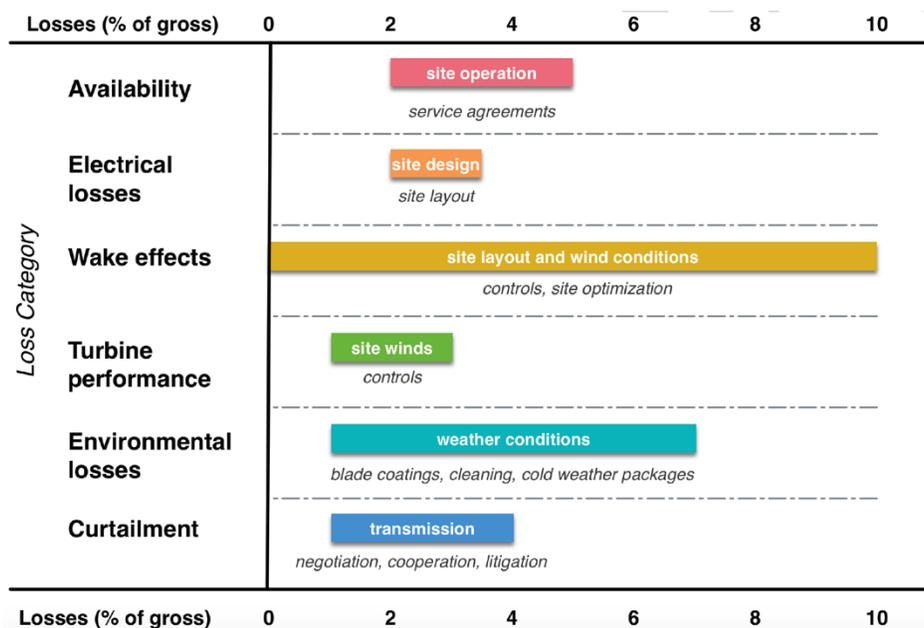


Figure 7. Range of typical project losses as a percent of gross production

4.1.2.1 Availability

Availability is the metric by which we understand how often the turbine is ready and able to produce power. Availability falls into three general categories: turbine, balance of plant, and grid. From the IEC specification for time-based availability, it is the “fraction of a given operating period in which a [wind turbine] is performing its intended services within the design specification.” Historically the industry has calculated availability as a time-based metric but has moved toward more energy-based availability calculations on the basis that the wind resource is variable and as such the turbine’s availability is more valuable during some periods than others. One of the main advantages of energy-based availability calculations is the ability to detect poorly scheduled maintenance.

Availability is measured using a variety of turbine status signals, as described in Section 4.1.1.2.

4.1.2.2 Wake Effects

Wake effects cover the loss of wind speed and increase in turbulence intensity as a result of upstream obstacles. From a utility perspective, wake losses are typically defined as a result of upwind turbines disturbing and slowing down the free stream wind speed. Wake can be generated internally (within the wind farm being studied) or externally (from a neighboring wind farm, if any). Additionally, there is the possibility of future wake effects as more wind turbines or wind farms are built. For small wind turbines, the wake is more often from buildings and other obstacles such as trees in the environment. It is also important to consider future wakes in this

environment over the 20-year life of the project—these will arise from installation of new structures and trees growing.

There is no standards-based way to estimate wake effect losses, but the typical utility industry approach is to model wind speeds at each location, calculate the turbine power output in that wind field, calculate the wakes from each turbine, and use the new wind speed to estimate power at each wind turbine location (Clifton, Smith, and Fields 2016). In the small wind industry, wake effects are approximated using rules of thumb, as described in Section 2.1.8.

There is no operational validation of wake losses in the utility or small wind industry.

4.1.2.3 Electrical

Electrical losses fall into two main categories: electrical efficiency and facility parasitic consumption. Specific losses include losses in collector lines, transformers, other site equipment, and transmission. These losses are therefore directly impacted by the site design.

This is the simplest loss parameter to quantify during project operation. It can be calculated by obtaining a power measurement at each turbine and another at the point of common coupling or the meter to capture the electrical losses between the point of generation and the distribution grid. It is the same procedure for utility-scale turbines or projects and small wind turbines.

4.1.2.4 Turbine Performance

Wind turbine power curves are typically generated from models and based on ideal conditions, which are not representative of average installed turbine conditions. Many factors may be included here: load- or noise-reducing control modes, high turbulence, high inflow, complex terrain, high wind shear or veer, and high-wind-speed hysteresis.

Turbines typically fall 1% to 4% short of advertised power curves under IEC-compliant conditions (Brower 2012).

Operational turbine performance is difficult to evaluate due to the lack of wind resource measurements measuring the free-stream wind speed in all directions at each turbine. However, utility projects have more funding to use remote sensing to validate operational performance and may have one or more onsite met towers to validate a performance and improve models.

Small wind turbines tend to lack operational wind resource measurements.

4.1.2.5 Curtailment

Curtailment is the deliberate management of the wind plant to reduce the amount of energy compared to what is possible from the available resource. This may occur because of grid limitations; environmental or permitting requirements (e.g., to prevent bird or bat deaths or to prevent flicker); or deliberate operational strategies, including directional curtailment/wind sector management.

For utility projects, curtailments are difficult to predict due to the high degree of uncertainty as to what may be built in the future (grid curtailments) and a lack of knowledge about a plant operator's future actions. Environmental curtailment is typically quantified during the permitting process and has less uncertainty. In addition to the difficulty in predicting and estimating

curtailment, these periods are difficult to filter out without having time series data for analysis; even with data, turbine signals that can clearly identify curtailment events are rare.

Curtailment is infrequent or nonexistent for small wind systems but may be applicable for single utility systems behind the meter.

4.1.2.6 Environmental

Environmental losses include those due to icing, blade degradation, environmental shutdown, and exposure due to changes in obstacles near the installed turbine, such as the growth or clearing of trees or the addition or destruction of surrounding buildings.

4.2 Recent Assessments

Two recent validation efforts quantify aggregate performance for commercial and distributed wind projects. Each study encompasses several hundred turbine-years. The first results are from an ongoing study at NREL and the second are from analysis at Pacific Northwest National Laboratory that looked at REAP and NYSERDA data.

4.2.1 Commercial Wind Projects: Results from the DOE's A2E Performance, Risk, and Uncertainty Framework

NREL recently began a study to evaluate the current performance of utility-wind project pre-construction energy estimates and validate the current third-party methodologies for energy yield assessments for the North American market. Figure 8 illustrates the preliminary findings of the study. The mean bias for a subset of North American wind projects from 2006 to 2016 is 10.8%. This represents an over-prediction of energy from the projects relative to their actual measured production. This 10.8% number controls for extreme events and long-term performance.

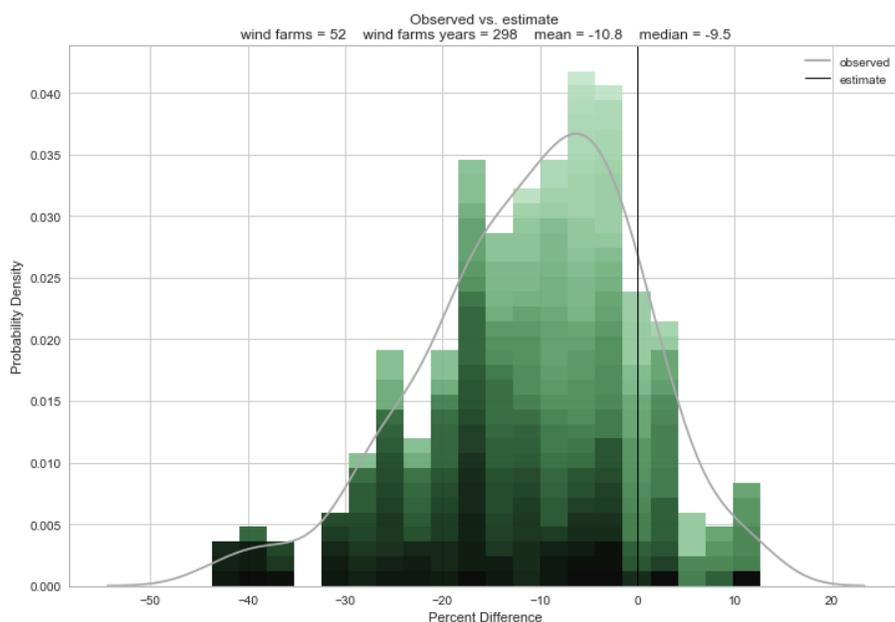


Figure 8. Preliminary results from the Performance, Risk, and Uncertainty Framework project

4.2.2 Distributed Wind Projects: REAP and NYSERDA Project Performance Results from the Distributed Wind Market Report

Figure 9 compares the actual versus projected performance for the REAP and NYSERDA projects broken out by turbine size class: small certified turbines, small non-certified turbines, mid-size turbines, and large turbines. The centerline in each box plot represents the median value for each turbine class. The whiskers show the extent of the first and fourth quartile for the data. The plots represent a different number of projects for each turbine class, as detailed in the *2017 Distributed Wind Market Report*.

Table 2. Project Volume for Each Turbine Class

Turbine Class	Number of Projects
Small: certified	129
Small: non-certified	105
Mid-size	7
Large	12

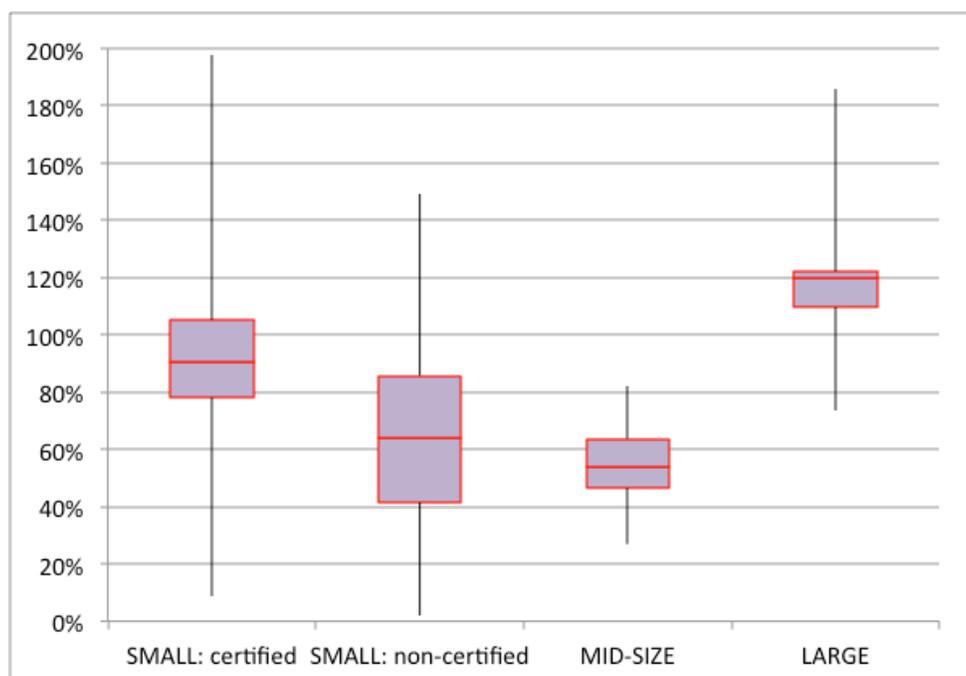


Figure 9. REAP and NYSERDA results: operational turbine performance vs. pre-construction energy estimate

The project-specific details that drive each project’s actual energy generation amounts were not available for review, but in general, the amount of annual energy production that can be achieved by a distributed wind project is driven by many variables, including the project’s available wind resource, siting, and availability.

In these datasets, the projects using large turbines over-perform compared to the projects’ projected performance at the time of incentive application.

In contrast, the projects using small and mid-size turbines in these datasets tend to underperform compared to the projects' projected performance. The limited sample size for the mid-size turbine class may account for some of the discrepancy between projected and actual performance for this turbine size class.

The certified small wind turbines exhibit a higher average of percent of projected production (89%) than the non-certified small wind turbines (64%), but this difference cannot be attributed solely to the turbine technology. Actual performance, compared to predicted performance, is driven by many factors including turbine technology, wind resource assessment methodologies, actual versus predicted wind resource, micro-siting issues, and turbine availability.

5 Sensitivity Analysis

Quantifying the impact of various resource parameters and loss categories on performance could enable DWRA professionals to make choices about which parameters need to be measured and to make rough assessments of the accuracy of models. For example, having accurate wind speed measurements has a large impact on the accuracy of estimated power production and barometric pressure has much less of an impact, but are there other parameters that are important? How much does a small error in parameter estimation impact the accuracy and uncertainty of the production estimate?

This effort comprised two separate activities: a qualitative analysis using the analytic hierarchy process and a quantitative analysis using FAST. Neither study has provided a conclusive, ordered list from which to make definitive selections for which parameters to measure and at which level of accuracy, but they have provided some initial insight into which elements are most important in this process.

5.1 Analytic Hierarchy Process

The interaction between site-specific details and wind resource parameters is myriad, nuanced, and complex. To begin to decouple the complex interactions, NREL conducted an expert elicitation utilizing the Analytic Hierarchy Process. Analytic Hierarchy Process is a structured technique for organizing and analyzing complex decisions, based on mathematics and human input.

For the Analytic Hierarchy Process, NREL assembled a group of wind industry experts that included turbine manufacturers, academics, consultants, and resource assessment specialists. The exercise was conducted in two parts. Part one was conducted with all study participants and NREL and DOE staff. The objective was to discuss the proposed list of wind resource and turbine input parameters for estimating turbine performance assessments and to determine whether there were missing or extraneous factors.

The initial discussion allowed each participant to weigh in on the proposed list of parameters. The group generally agreed on the list of resource factors, although all participants mentioned the variability in relative impact depending on the configuration of a site. From this discussion, it appeared that of the turbine input parameters, turbulence and density had little impact (a few percent each) on turbine performance relative to the wind speed and could therefore be ignored. Veer—the variability in wind direction—came up as a factor that impacts performance for multi-megawatt turbines but probably has little impact on small or mid-size turbine performance. Overall, the discussion highlighted the complexity inherent in estimating performance, given the breadth of the distributed wind industry turbine sizes and factors such as turbine availability, site complexity, and a specific turbine's control mechanisms.

Based on the results of part one, part two of the analysis focused on the parameters that impact the turbine location wind speed (of which there were five key parameters: off-site or reference wind speed, wind shear, obstacles, roughness, and elevation contours). The Analytic Hierarchy Process framework was applied to these remaining parameters. Wind direction was removed from the sensitivity analysis because rather than impacting the turbine output, it is the spatial framework by which all other parameters must be analyzed. This is easiest to visualize in the

case of obstacles but is true for all other parameters. Figure 10 shows all the parameters that were considered during the analysis.

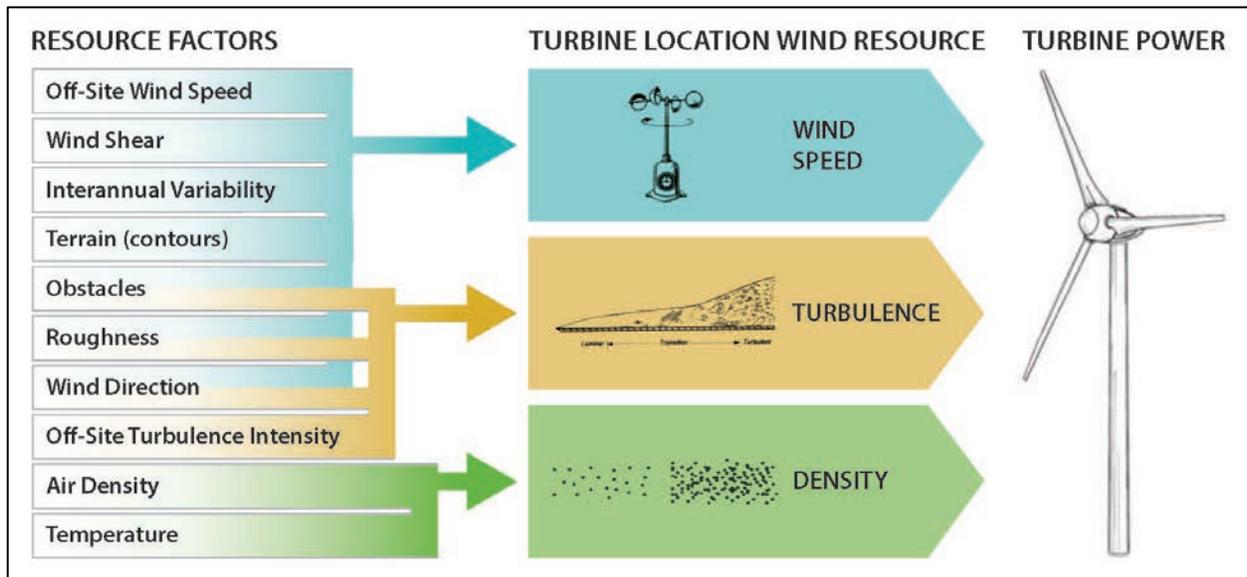


Figure 10. Resource and turbine input parameters presented for consideration

Table 3 through Table 5 show the results from the expert elicitation. Table 3 is the approximate contribution from the three elements assumed to impact turbine power output. Table 4 presents the results of the Analytic Hierarchy Process, showing the median value (the relative impact or contribution) for each of the five parameters based on the 10 participant responses.

Table 5 provides the weighted average of the full list of resource factors. Figure 11 illustrates the percentage contribution for the top five factors listed in Table 5.

Table 3. Turbine Input Parameters

Input Variables	Contribution %
Turbine Location Wind Speed	90%-96%
TI	~2%-5%
Density	~2%-5%

Table 4. Resource Factors that Impact Turbine Location Wind Speed

Input Variables	Contribution %
Offsite/Reference wind speed	45.8%
Obstacles	23.2%
Contours	16.9%
Roughness	9.1%
Wind shear	8.6%

Table 5. Resultant Contribution

Input Variables	Contribution %
Wind direction	Outside of analysis
Reference wind speed	41.2%
Obstacles	20.9%
Contours	15.2%
Roughness	8.1%
Wind shear	7.7%
TI	~2%-5%
Density	~2%-5%

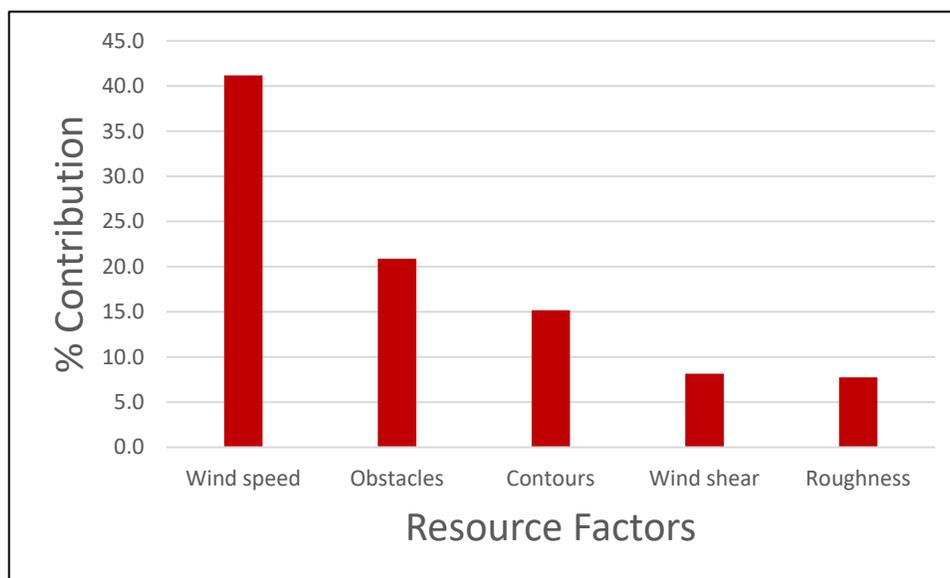


Figure 11. Contribution from top five resource assessment factors

5.2 FAST Analysis

The analysis utilized FAST (Jonkman) for power performance predictions of turbines under different wind conditions and a technique called elementary effects, a simple methodology for screening parameters and assessing sensitivity to different wind conditions. The sensitivity analysis is based on a one-at-a-time approach in which each parameter of interest is varied individually while holding all other parameters fixed. The study evaluated the impact of wind speed, turbulence, air density, wind veer (change in wind direction with height), shear stability class, and roughness for four turbine models available in FAST and typical ranges for each parameter.

Wind turbine power curves are estimated using the average binned wind speeds at hub height as suggested by the IEC (IEC 2005). However, several other meteorological parameters such as wind shear, turbulence intensity, wind veer, and changes in air density are expected to influence the certified power curves (Farkas 2011). While emphasis is placed on accurate wind speed measurements at hub height, these additional atmospheric conditions can also play a role in turbine productivity. So far, few studies have attempted to evaluate these sensitivities for small

turbines. This analysis examined the effects of these other atmospheric conditions on power performance of small wind turbines in an effort to reduce uncertainties in performance estimates for small turbines. NREL’s Turbsim (Kelley and Jonkman) was used to simulate different sets of stochastic full field turbulences that the turbines may encounter during normal operation. These wind fields were then used to simulate and analyze the power output for four small wind turbines, including a three-blade horizontal-axis rotor, pitch and stall regulated, upwind and downwind rotor turbines using NREL’s aero-servo-elastic tool, FAST (Jonkman). FAST provided estimates for turbine power response for three sets of wind speed bins and atmospheric stability.

Four turbines—T-1, T-2, T-3, and T-4—were chosen to represent the range of distributed wind turbines. These turbines were rated at 10 kW, 85 kW, 225 kW, and 1.5 MW; the main specifications are listed in Table 6.

Table 6. Basic Specifications for the Four Turbines Analyzed

Turbine	T-1	T-2	T-3	T-4
Rating	10 kW	85 kW	225 kW	1,500 kW
Hub height	25.0 m	43.21 m	31.5 m	80 m
Rotor diameter	6.7 m	19.2 m	27 m	77 m
Cut-in wind speed	3.1 m/s	4.0 m/s	3.0 m/s	3.1 m/s
Cut-out wind speed	none	25 m/s	25 m/s	25 m/s
Power control	Fixed pitch	Stall	Pitch	Pitch

T-1 is a three-bladed, fixed pitch, small furling wind turbine with a rated output power of 10 kW (Corbus and Meadors 2005). T-2 is a stall-regulated, three-bladed, horizontal-axis downwind turbine. T-3 is a fixed speed, variable pitch, three-bladed wind turbine. T-4 is a variable speed, variable pitch, three-bladed upwind wind turbine. The power performance curves for these turbines are shown in Figure 12.

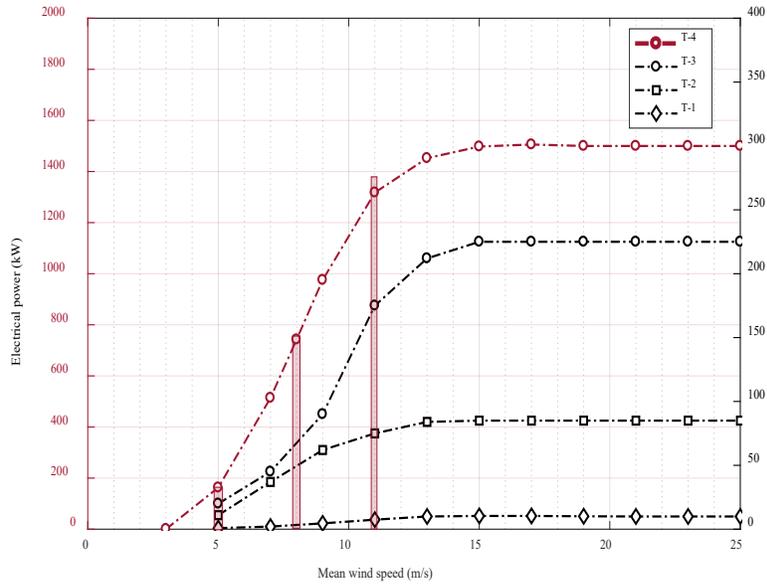


Figure 12. Power performance curves for turbines T-1 through T-4

To examine the potential sensitivities of mean power performance of these turbines to different wind conditions, the team used the elementary effects approach adopted by Robertson et al. (2018). Elementary effects is a screening method in sensitivity analysis (Saltelli et al. 2008) that provides for qualitative sensitivity analysis measures to rank input factors in order of their importance. Each parameter of interest is varied individually while holding all other parameters fixed. A derivative is then calculated based on the measured change in mean power (or standard deviation in power) for a measured change in the input parameter (e.g., shear). The change in power statistics for a given input parameter is examined at different locations in the input parameter hyperspace. In other words, only one parameter is varied at a time, but this variation is performed multiple times using different values for the other input parameters.

5.2.1 Approach

The following describes the analysis procedure for T-1, which was repeated for all four turbines.

For the purpose of this analysis, 19 relevant wind parameters were chosen to represent the variety of inflow conditions that the turbines may encounter during operation. Eighteen of these parameters were chosen based on NREL’s prior study on wind parameter sensitivity by Robertson et al. (2018). The study utilized the Veers model for describing and generating the wind characteristics for simulating the wind turbine. The model entails 18 parameters described by the mean wind profile (defined using two parameters: wind shear, α , and wind veer, β), velocity spectrum (defined using integral length scale parameters for the three velocity components L_k , and standard deviations σ_k with $k = u, v$ and w), point-to-point spatial coherence (defined using decrement and offset parameters a_k and b_k and coherence exponent γ), and component-to-component correlations (PC_{uv} , PC_{vw} , PC_{uv}). Furthermore, air density was included to study variation from the standard value ($\rho=1.0$ kg/m³).

The parameters were binned on three mean wind speeds at hub height, from cut-in to near-rated, as well as atmospheric stability for neutral (N), stable (S), and unstable (U) conditions.

The basic approach for performing an elementary effects analysis requires a sampling of the 19 parameters and different starting evaluation points where derivatives are calculated to obtain a good assessment of their overall sensitivity. The sampling was designed to represent all possible values that the parameter of interest could assume (e.g., α). Then an approach to vary the parameters was selected. This study used the Sobol sequence for starting points. (Sobol sequences belong to the family of quasi-random sequences that are designed to generate samples of multiple parameters as uniformly as possible over the multi-dimensional parameter space.)

The goal was to develop understanding of the sensitivity of power performance, say Y_o (particularly, mean and standard deviation in power), to different combinations of the 19 input parameters.

$$Y_o = f(U_1, U_2 \dots U_{19}) \quad (1)$$

For a given sampling of an input parameter U_i , the elementary effect of U_i on Y_o is found by varying U_i by a normalized amount, Δ_{ibs} such that

$$EE_{ib} = \frac{Y_o(U_1, \dots, U_{ib-1}, U_{ib} + \Delta, U_{ib+1}, \dots, U_{19}) - Y_o(U_1, U_2, \dots, U_{19})}{\Delta_{ibs}} \quad (2)$$

$Y_o(U_{ib})$ the average of mean /standard deviation of electrical power in wind speed bin ‘b’ across ‘s’ random realizations for a certain input parameter, $i = \{\alpha, \beta, L_u, L_v, L_w, \sigma_u, \sigma_v, \sigma_w, a_u, a_v, a_w, b_u, b_v, b_w, \gamma, PC_{uw}, PC_{uv}, PC_{vw}, \rho\}$

$$\Delta_{ibs} = \pm 0.1 * (U_{ibmax} - U_{ibmin}) \quad (3)$$

The method provides two sensitivity measures for each input factor. The mean of EE_{ib} denoted by μ_i^* is helpful for assessing the overall importance of an input factor on the model output; and standard deviation of EE_{ib} denoted by σ_i describes non-linear effects and interactions between the parameters. Since we are interested in screening the parameters, we chose to examine the mean of elementary effects and used it as a measure for sensitivity. If there are R different sampling points, the mean of the absolute value of EE_{ib} across R different sampling points is given by

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^R |EE_{ib}^j| \quad (4)$$

The sensitivity analysis was run three times across three wind regions, assuming a mean wind speed within each bin (5, 8, and 11 m/s). The process was repeated three times for each wind speed bin representing the different stability conditions. An accurate stratification of atmospheric stability will depend on several wind parameters, and there are different indices that can be used (e.g., the gradient (or bulk) Richardson number, and the Monin-Obukhov length, L). Depending on which metric is used and the approach applied to compute the index, they can generate quite different stability climates (Barthelmie 2015). For this study, measurements or models for virtual heat flux changes necessary to derive estimates of L were not available. To simplify the problem, three stability conditions were defined based on shear, turbulence intensity, and integral length scales. It was assumed that stable conditions were associated with combinations of low turbulence and high shear. Integral length scales were assumed to be relatively small, resulting in narrower wakes in stable conditions. Unstable conditions were characterized by high turbulence

and low shear. In addition, large integral length scales were assumed to act to widen wakes. Moderate shear and turbulence represented neutral conditions with intermediate values assumed for integral length scales.

For each of the parameter settings identified, 10 turbulent wind files (i.e., independent time-domain realizations from 10 seeds) were generated in TurbSim. A 6 x 6 square grid was considered to span the entire rotor plane of the turbine. FAST was then used to simulate a model of the 10-kW wind turbine using the wind files developed. Besides normal aero-elastic features of FAST, furling capability was enabled (Jonkman and Hansen). For the analysis, 19 parameters with 50 starting points were examined. From the 10 turbulence seeds for each sampled parameter space, the sensitivity analysis was conducted nine times (three wind speed bins (w) times stability classes). In total, 90,000 simulations were performed. Table 7 illustrates the min/max range used for turbine T-1.

Table 7. Parameter Definitions for T-1 for Sensitivity Analysis

Mean velocity	Mean wind profile		Velocity spectra, turbulence standard deviations						Spatial coherence parameters and component-to-component velocity correlations (Turbulence)									Air density		
	α	β	L_u	L_v	L_w	σ_u	σ_v	σ_w	a_u	a_v	a_w	b_u	b_v	b_w	γ	PC_{uw}	PC_{vw}		PC_{uv}	ρ
Class		5 m/s																		
N	min	0.1	-5	100	100	100	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	5	124	124	70	0.65	0.65	0.3	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	5.0	4.0	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	5	20	15	10	0.495	0.495	0.2	7.0	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	160	135	135	0.655	0.655	0.655	7.0	2.5	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	5	200	200	100	3.0	3.0	2.0	8.0	5.0	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
Class		8 m/s																		
N	min	0.1	-5	71	71	71	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	5	240	240	120	0.65	0.65	0.3	7.0	3.0	3.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	8.0	2.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	5	70	70	35	0.495	0.495	0.2	10	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	241	241	241	0.655	0.655	0.655	12	10	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	5	400	400	400	3.0	3.0	2.0	15	12	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
Class		11 m/s																		
N	min	0.1	-5	71	71	71	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	5	240	240	120	0.65	0.65	0.3	7.0	3.0	3.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	8.0	2.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	5	70	70	35	0.495	0.495	0.2	10	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	241	241	241	0.655	0.655	0.655	12	10	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	5	400	400	400	3.0	3.0	2.0	15	12	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15

From each simulation, the power response (mean and standard deviation of electric power) was extracted and averaged across the 10 seeds. The elementary effect of each parameter on power response was then computed using (2). The mean of elementary effects given by (4) was then computed for each bin across all stability classes. The parameters that resulted in highest values of the mean elementary effects were identified as outliers using the 2-sigma rule. Figure 13 shows a sample histogram of elementary effects-means for mean electric power for a single bin during neutral stability conditions. A count of the total number of outliers contributed by each parameter was then extracted to rank relative sensitivities.

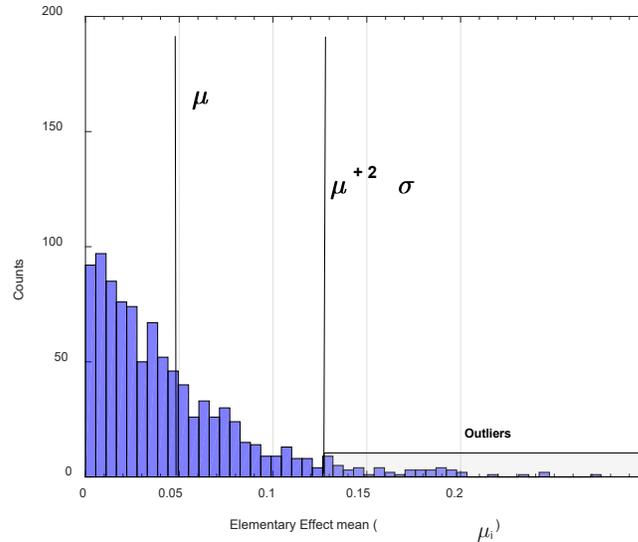


Figure 13. Sample histogram of mean elementary effects of all parameters on mean electric power

5.2.2 T-1 Results

For the 10-kW turbine T-1, air density and veer have the greatest impact on power performance in stable and neutral atmospheric conditions. In unstable atmospheric stability, secondary turbulence parameters become more dominant and more evenly impactful. Across all wind speed bins, standard deviation of electric power is most sensitive to u-component velocity standard deviation (TI). Table 8 identifies the top parameters across all three bins for T-1 identified as the top 25% of the total number of outliers (based on the 2-sigma rule explained above) across all stability classes.

Table 8. Sensitivity Ranking for T-1 Based on the Total Number of Appearances

Response	Bin 1		Bin 2		Bin 3	
	1	2	1	2	1	2
Power-mean	ρ	β	ρ	-	ρ	β
Power-standard deviation	σ_u	-	σ_u	-	σ_u	L_u

Figure 14 illustrates the impact of stability classes on mean power for T-1 predicted for a certain combination of parameters at an air density of 1.05 kg/m³. A significant reduction at 8 m/s and 11 m/s is observed when wind conditions are unstable, whereas a marginal increase in power at 11 m/s is noted when conditions were stable.

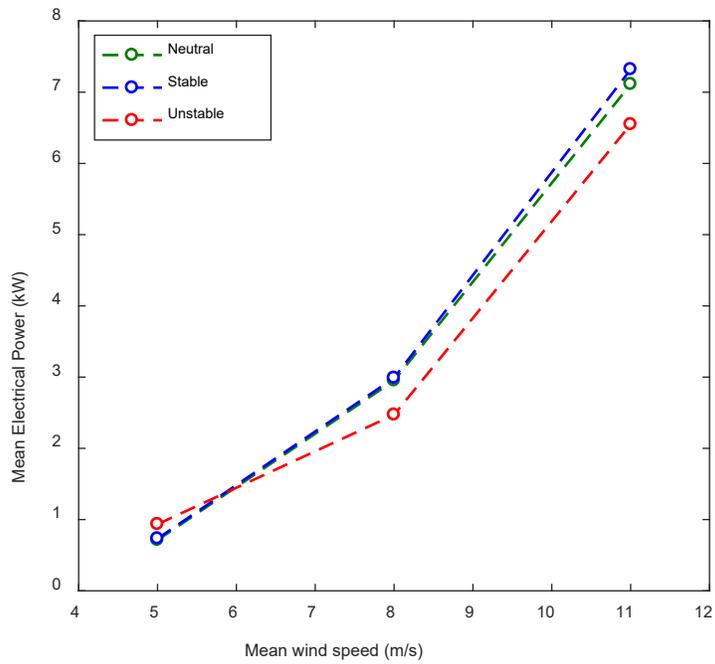


Figure 14. T-1 sensitivity to stability

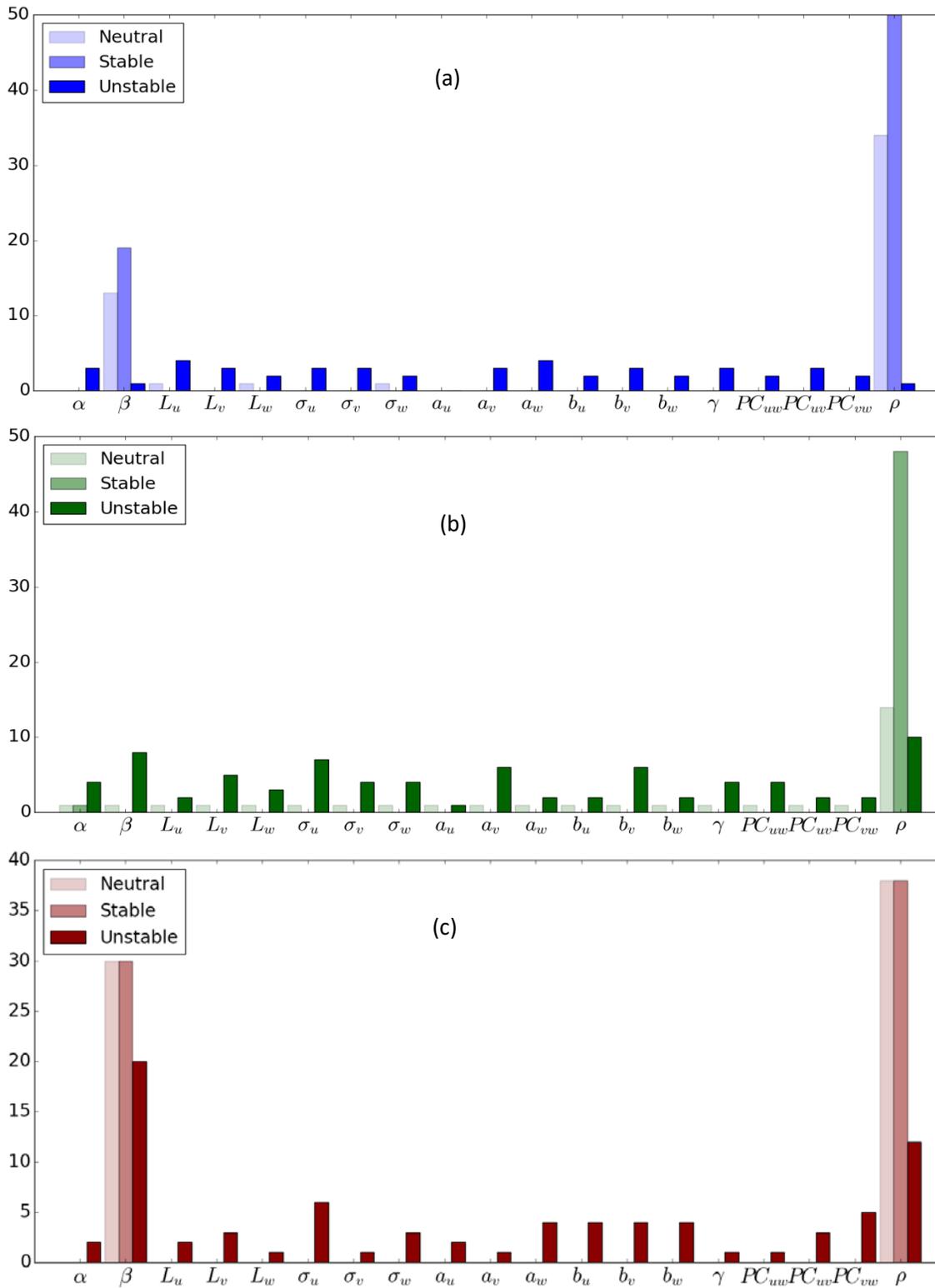


Figure 15. Sensitivity rankings of mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

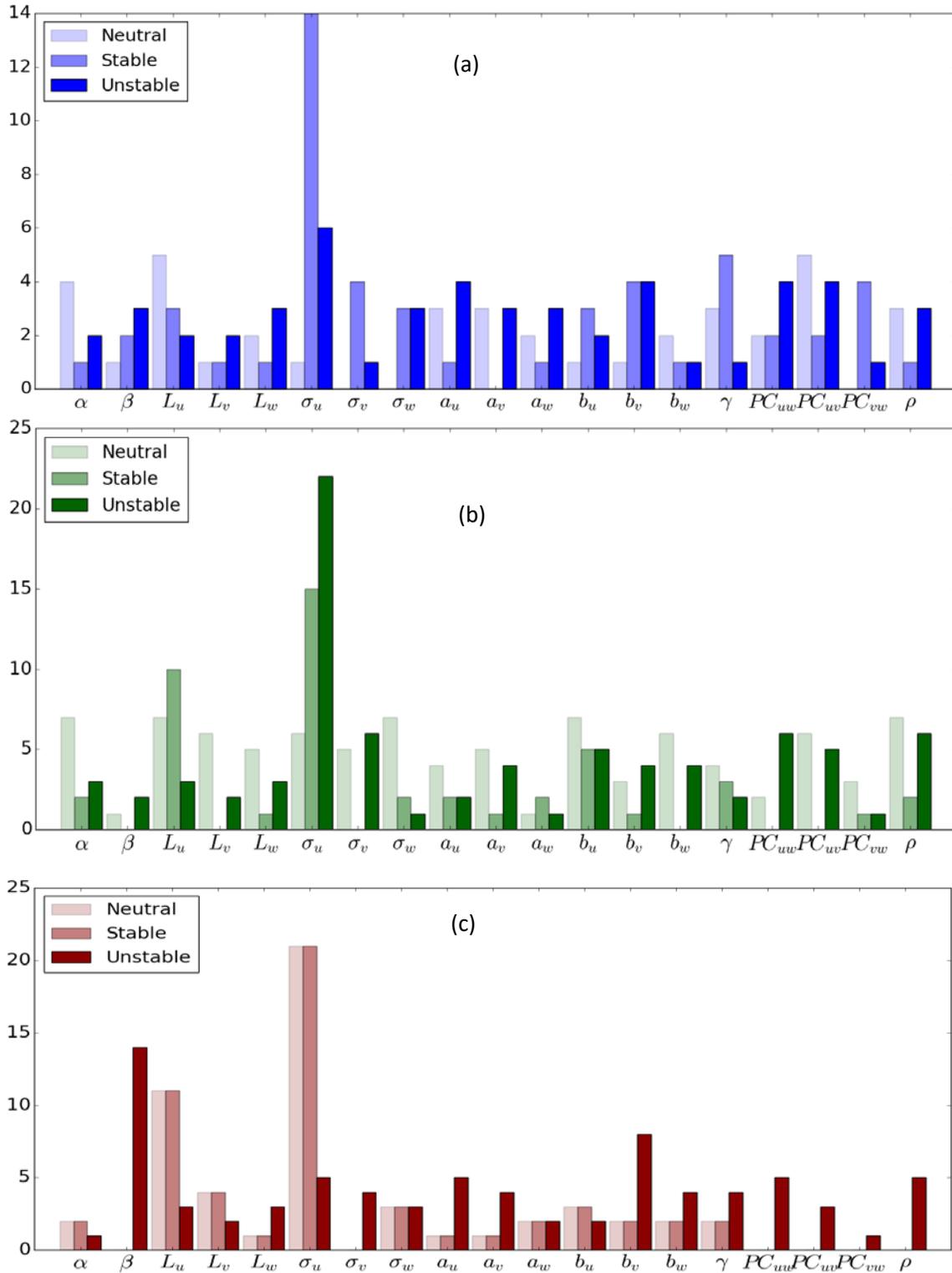


Figure 16. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

5.2.3 T-2 through T-4 Results

Results for turbines T2-T4 are detailed in Appendix A and follow the same pattern as turbine T-1. For each turbine, there is a table detailing the most impactful resource assessment parameters, a graph illustrating the impact of stability on power performance, and then two pages of plots illustrating the contribution of each input parameter on power output for the three wind speed and three atmospheric stability classes.

Changes to air density has the most impact on power performance for turbines T-2 and T-3 in stable and neutral atmospheric conditions. However, in unstable atmospheric stability, secondary turbulence parameters become more dominant for T2 and T3, similar to T1. For T-4, secondary turbulence parameters dominate in all atmospheric conditions, resulting in power performance being relatively insensitive to changes in air density.

It may be inferred that air density, standard deviation (TI), and to a lesser degree atmospheric stability have the most influence on turbines T-1 through T-3. The behavior is markedly different in T-4, in which veer, shear and TI are prominent in all wind speed cases that were examined. The stability stratification is apparent in all the turbines.

6 Benchmark Datasets

Developing independent validation datasets that highlight key DWRA-specific conditions is critical for assessing project performance estimation models because it is unusual for distributed wind turbine installations to have operational wind resource measurements, turbine status signals, or power measurements. The portfolio should include a variety of site configurations covering a range of conditions; e.g., flat to complex terrain, open prairies to forested regions, and open fields to urban environments. It should also cover a variety of commercially available turbine types.

NREL is collecting datasets for this purpose, beginning with datasets from the small wind turbine testing centers across the country and other public institutions. These datasets are generally in terrain that is relatively benign, due to the nature of power performance testing requirements. There is still a need to discover datasets with turbine power and wind resource measurements in areas of complex terrain.

If you have a dataset you would like to contribute to this compendium, please email NREL through the WINDEXchange website or at windexchange@nrel.gov.

7 Conclusions and Recommendations

The team has identified the key parameters of a DWRA performance framework, including key wind resource parameters, operational measurements, losses, and uncertainties. This framework could be used as the foundation for understanding the predictability of the power and revenue from a project. Improving the predictability and reliability of wind power generation and operations could reduce costs and potentially establish a framework to attract new capital into the wind energy space.

In general, improving the accuracy of DWRA performance predictions could reduce costs by:

- Improving the overall distributed wind fleet performance
- Enabling a reliable tiered screening methodology, with different methodologies available depending on the level of complexity of the site under consideration and the level of accuracy required by project developers and financial stakeholders
- Reducing the cost of capital and project financing by decreasing project risks through better precision and accuracy of energy predictions
- Expanding state or federal incentive support through improved and consistent project performance.

However, before performance estimates can be improved, we need to understand how accurate the industry's current estimates are today. In the process of documenting the key parameters, it became clear that many of the adjustments to the raw wind speed and other parameters are based on rules of thumb or expert experience. It is likely that expert analysts within a region have a good sense of how to apply these adjustments, but a more rigorous approach to analyzing key parameters is needed as practitioners expand their market space, new individuals and businesses join the industry, and alternative financing mechanisms are considered.

The above discussion details the various approaches, tools, and models used to assess the wind resource at a prospective site, the expected energy production, and how to evaluate the accuracy of production estimates. It also lays out the distributed wind-specific gaps, challenges, and opportunities. Seeing the three primary methods for resource assessment mapped side by side, illustrated in Figure 1, it is easier to identify differences between the processes and where there may be tools or processes that can be distilled from the larger wind project approaches. Some of the key parameters and losses are being accounted for in the distributed wind space, while others are not.

The sensitivity analysis is one step toward developing a clearer understanding of the priority and required accuracy for the identified parameters but will require further investigation to understand the ultimate impact on project economics. From the analysis, it was clear that wind speed and direction are essential parameters for any performance estimate, followed by air density, veer, and turbulence intensity, particularly for small wind turbines. While density doesn't vary greatly on a particular site, the air density varies significantly across the United States, and developing a better understanding impact of density on the power performance of commercially available wind turbines will be highly valuable.

The next step for our collective understanding is to quantify the accuracy of each approach or tool and develop a consistent way to communicate this information with various stakeholders. Some of the tasks could include:

- Validating existing models to understand their limitations and appropriate uses
- Assessing current rules of thumb
- Verifying the entire site assessment process, not just the models used to perform site assessment
- Combining the results of multiple research efforts to provide better industry-wide guidance on modeling methodologies and appropriate assumptions
- Improving and better documenting methodologies for interannual variability assessment; understanding under which conditions the different methodologies are most applicable
- Performing additional sensitivity analysis on resource parameters
- Evaluating costs associated with various resource assessment methods
- Estimating uncertainty and financial impact of the various evaluation methods
- Building a decision matrix to aid in determining the most appropriate resource assessment method
- Developing distributed wind-specific loss and uncertainty frameworks
- Curating standard test cases and guidelines to facilitate discussion of which tools, processes, and methodologies are appropriate for specific site conditions and the limitations of various approaches
- Documenting potential project size thresholds that warrant different levels of assessment processes.

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Appendix

T-2 Results

For the 85-kW turbine T-2, only density stood out from the other parameters as having a large impact on turbine power performance during stable and neutral atmospheric stability.

Table 9. Sensitivity Rankings for Turbine T-2

Response	T-2					
	Bin 1		Bin 2		Bin 3	
Ranking	1	2	1	2	1	2
Power-mean	ρ	-	ρ	-	ρ	-
Power-standard deviation	σ_u	-	σ_u	b_w	ρ	σ_u

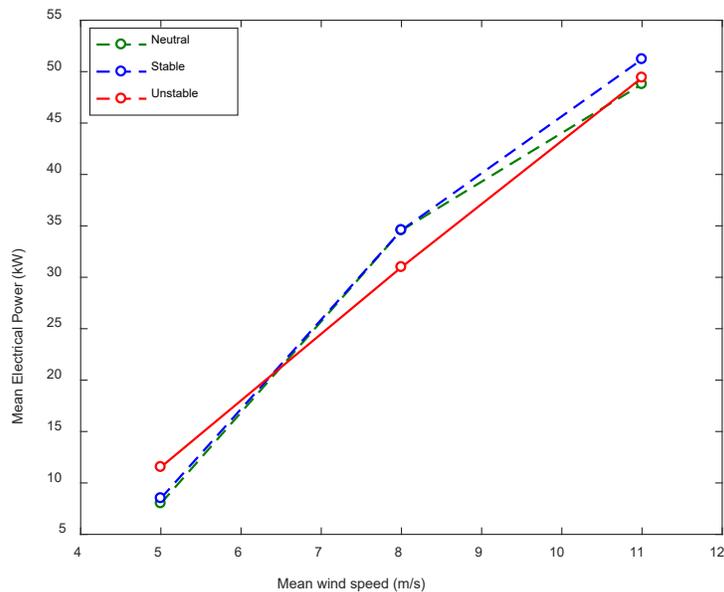


Figure 17. T-2 sensitivity to stability

Table 10. Parameter Definitions for Simulating T-2

Mean velocity	Mean wind profile		Velocity spectra, turbulence standard deviations						Spatial coherence parameters and component-to-component velocity correlations (Turbulence)										Air density	
	α	β	L_u	L_v	L_w	σ_u	σ_v	σ_w	a_u	a_v	a_w	b_u	b_v	b_w	γ	PC_{uw}	PC_{vw}	PC_{vw}		ρ
Class	5 m/s																			
N	min	0.1	-5	100	100	100	0.50	0.50	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	124	124	70	0.65	0.65	0.3	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	5.0	4.0	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	15	20	15	10	0.50	0.50	0.2	7.0	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	160	135	135	0.66	0.66	0.66	7.0	2.5	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	200	200	100	3.0	3.0	2.0	8.0	5.0	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
8 m/s																				
N	min	0.1	-5	71	71	71	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	240	240	120	0.65	0.65	0.3	7.0	3.0	3.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	8.0	2.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	15	70	70	35	0.49	0.49	0.2	10	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	241	241	241	0.66	0.66	0.66	12	10	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	400	400	400	3.0	3.0	2.0	15	12	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
11 m/s																				
N	min	0.1	-5	71	71	71	1.1	1.1	1.1	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	240	240	120	1.43	1.43	0.75	7.0	3.0	3.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.11	0.11	0.11	8.0	2.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.6	15	70	70	35	1.09	1.09	1.09	10	5.0	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.1	-5	241	241	241	1.44	1.44	1.44	12	10	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	400	400	400	2.5	2.5	1.75	15	12	5.0	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15

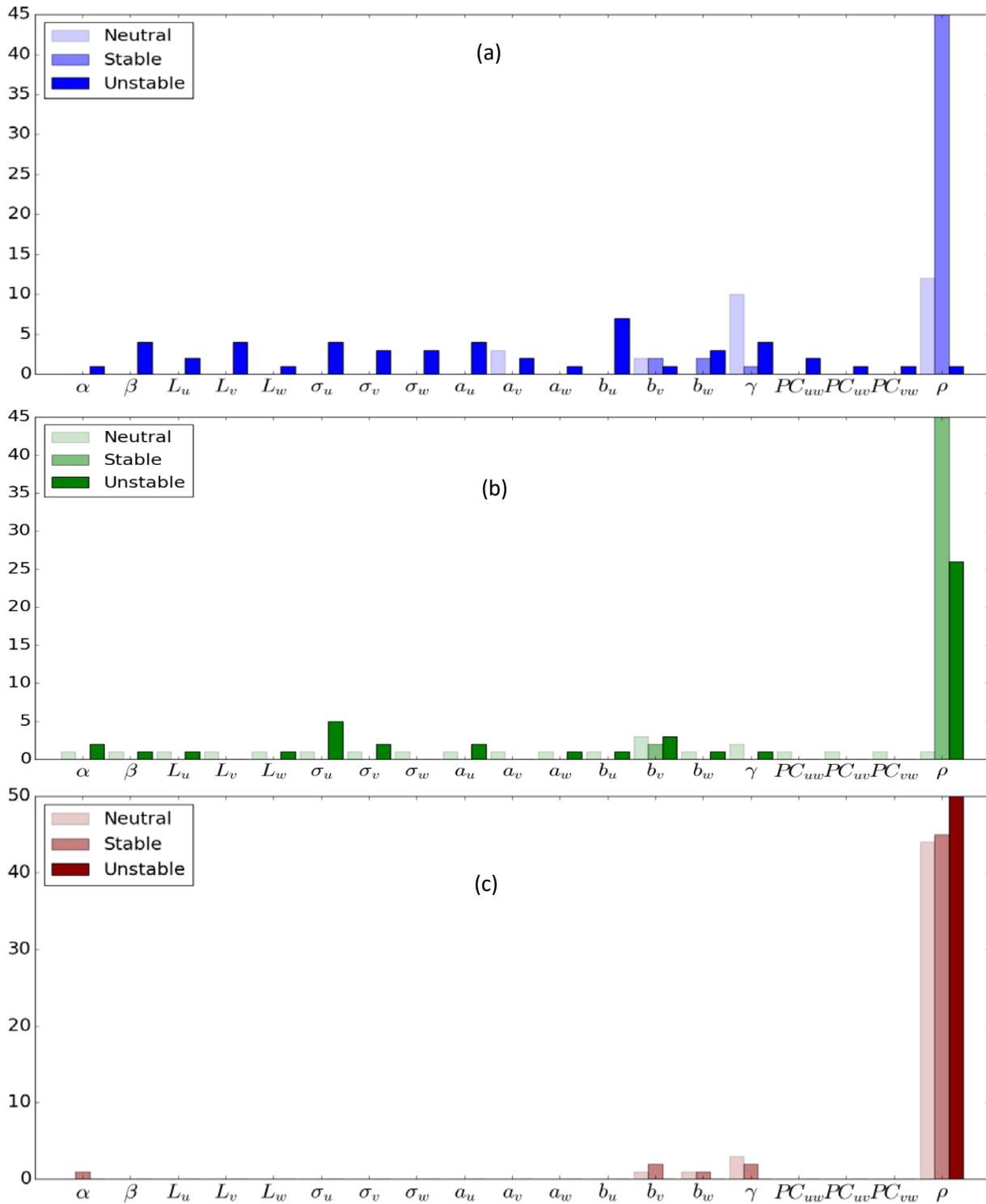


Figure 18. Sensitivity rankings for mean electric power to different wind parameters (1) Bin 1 (b) Bin 2 (c) Bin 3

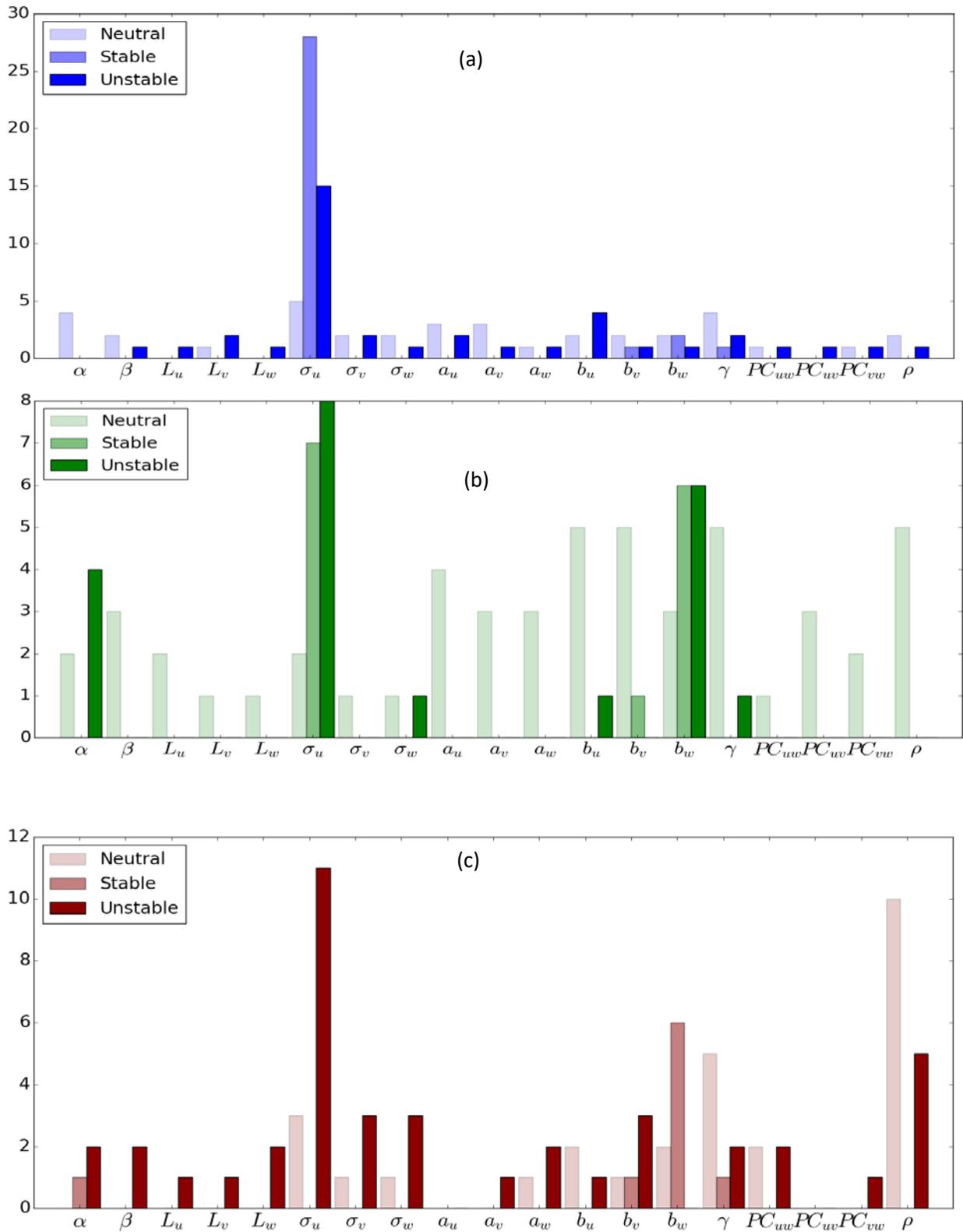


Figure 19. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

Results T-3

For the 225-kW turbine T-3, air density stood out from the other parameters as having the biggest impact on turbine power performance.

Table 11. Sensitivity Rankings for Turbine T-3

Response	T-3					
	Bin 1		Bin 2		Bin 3	
Ranking	1	2	1	2	1	2
Power-mean	ρ	-	ρ	-	ρ	-
Power-standard deviation	ρ	L_u	ρ	b_u	ρ	σ_u

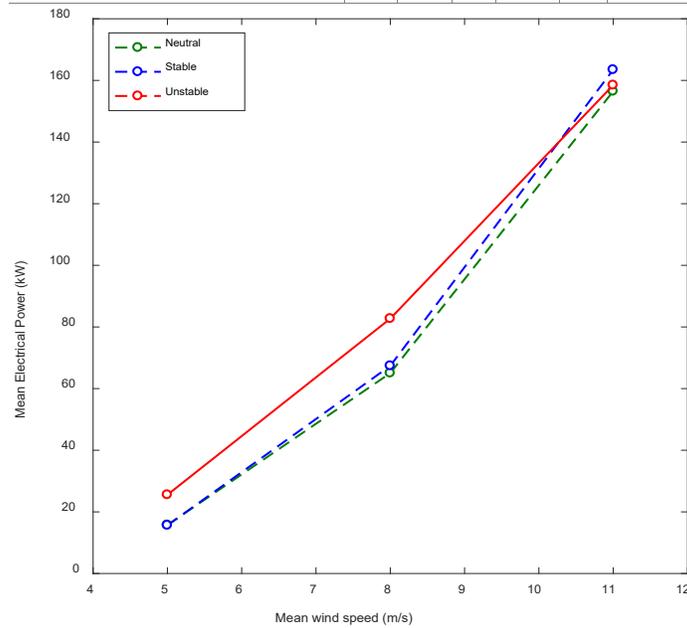


Figure 20. T-3 sensitivity to stability

Table 12. Parameter Definitions for Simulating T-3

Mean velocity	Mean wind profile		Velocity spectra, turbulence standard deviations						Spatial coherence parameters and component-to-component velocity correlations (Turbulence)									Air density		
	α	β	L_u	L_v	L_w	σ_u	σ_v	σ_w	a_u	a_v	a_w	b_u	b_v	b_w	γ	PC_{uw}	PC_{vw}	PC_{vw}	ρ	
Class	5 m/s																			
N	min	0.1	-5	100	100	100	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	124	124	70	0.65	0.65	0.3	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min		-5	2	2	2	0.05	0.05	0.05	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max		15	20	15	10	0.495	0.495	0.2	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	160	135	135	0.655	0.655	0.655	1.5	1.5	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	200	200	100	3.0	3.0	2.0	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
8 m/s																				
N	min	0.1	-5	71	71	71	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	240	240	120	0.65	0.65	0.3	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.05	0.05	0.05	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	15	70	70	35	0.495	0.495	0.2	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	241	241	241	0.655	0.655	0.655	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	400	400	400	3.0	3.0	2.0	5	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
11 m/s																				
N	min	0.1	-5	71	71	71	1.1	1.1	1.1	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	15	240	240	120	1.43	1.43	0.75	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
S	min	0.2	-5	2	2	2	0.11	0.11	0.11	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.0	15	70	70	35	1.09	1.09	1.09	5.0	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15
U	min	-0.8	-5	241	241	241	1.44	1.44	1.44	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	15	400	400	400	2.5	2.5	1.75	5	2.5	2.5	0.08	4.5e-3	0.011	1	0.5	6.0	1.0	0.15

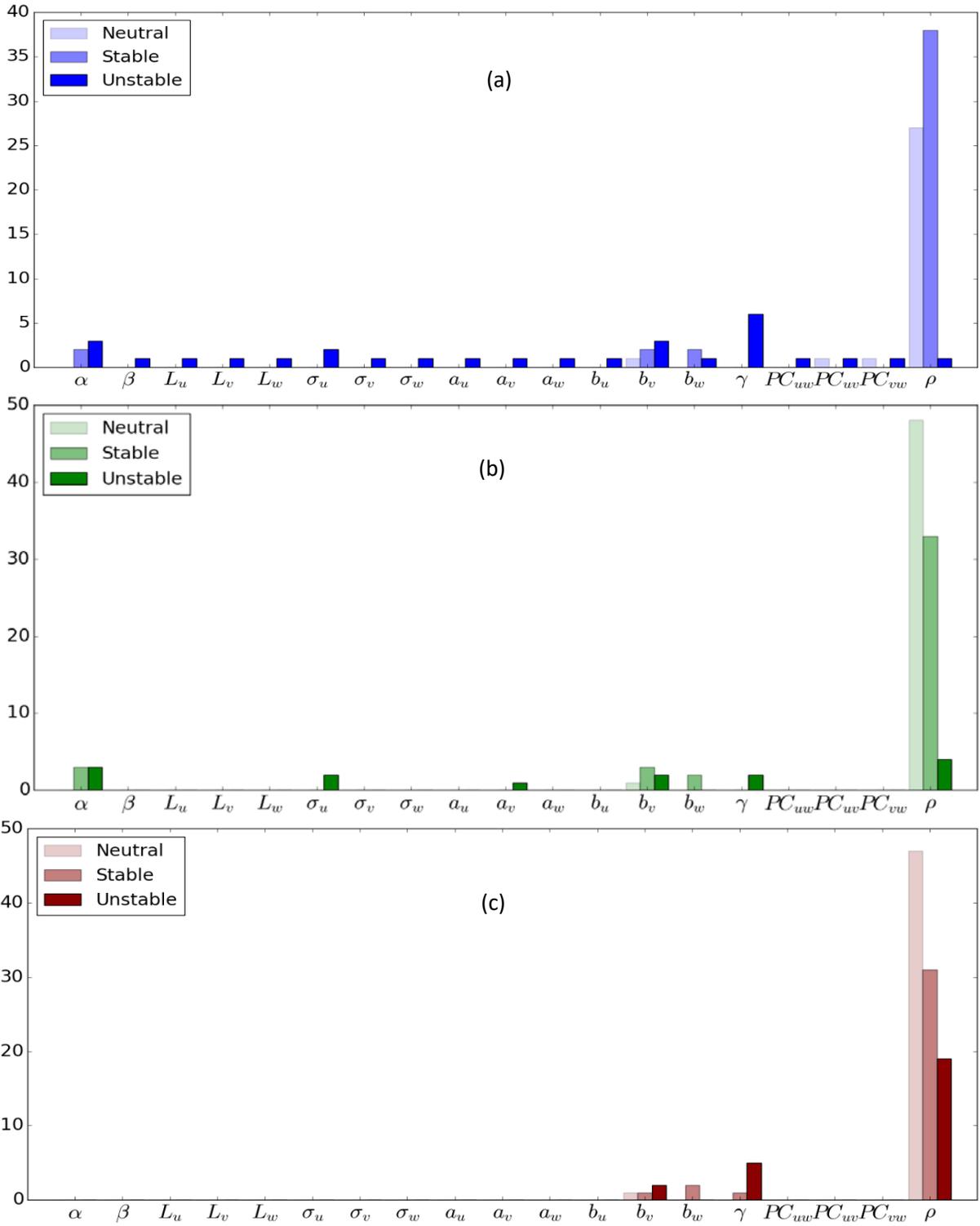


Figure 21. Sensitivity rankings for mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

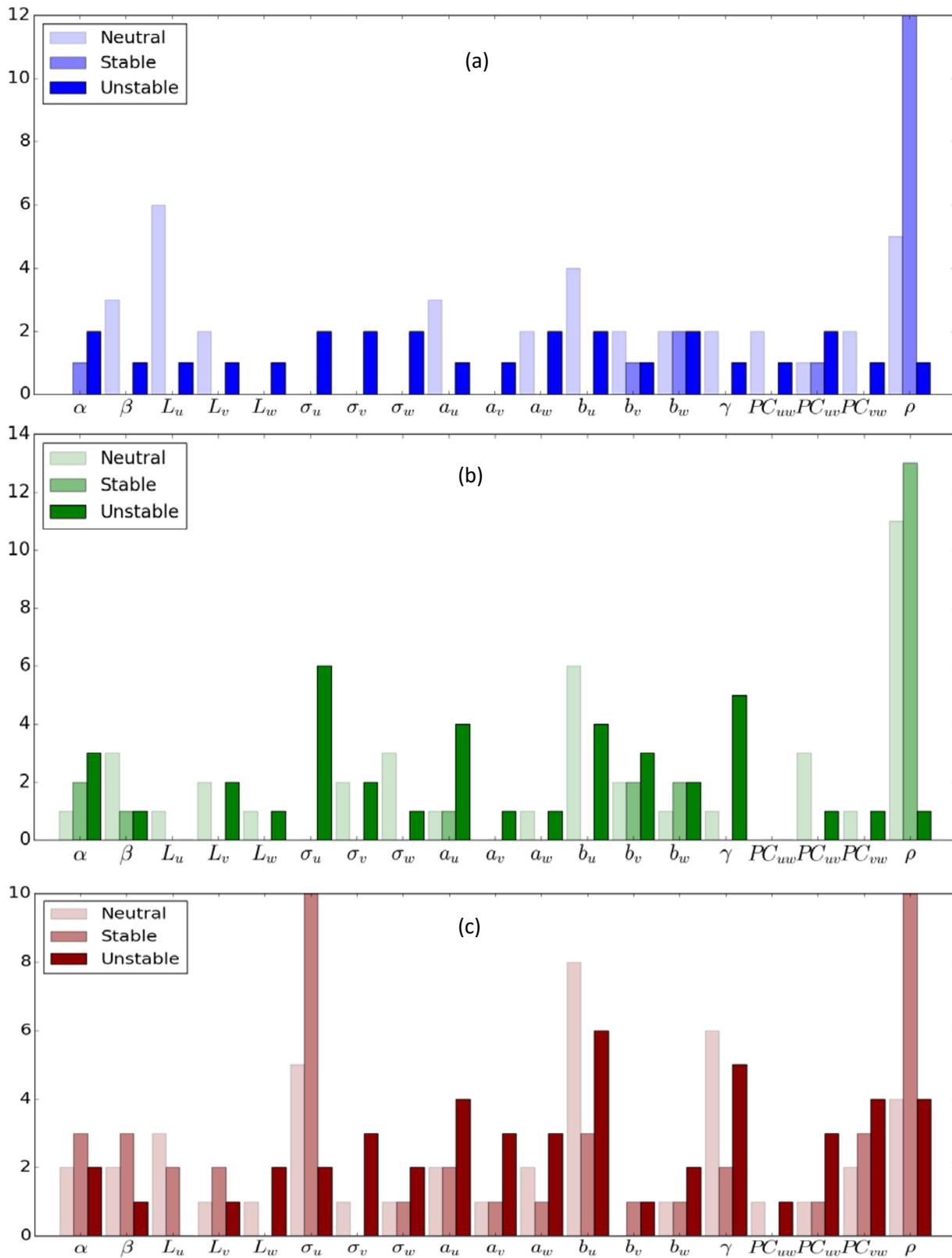


Figure 22. Sensitivity rankings for standard deviation in electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

Results T-4

For the 1.5-megawatt turbine, wind veer stood out from the other parameters as having the biggest impact on turbine mean power whereas turbulence had the most impact on standard deviation.

Table 13. Sensitivity Rankings for Turbine T-4

Response	T-4					
	Bin 1		Bin 2		Bin 3	
Ranking	1	2	1	2	1	2
Power-mean	β	α	β	α	β	σ_u
Power-standard deviation	σ_u	-	σ_u	-	σ_u	-

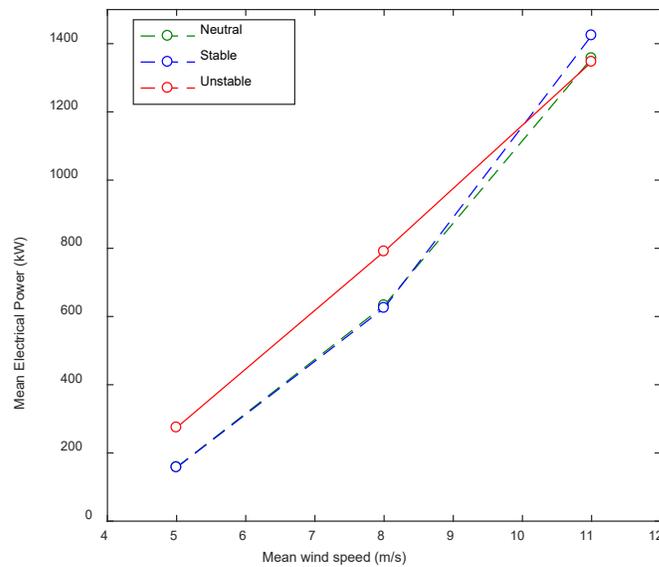


Figure 23. T-4 sensitivity to stability

Table 14. Parameter Definitions for Simulating T-4

Mean velocity	Mean wind profile		Velocity spectra, turbulence standard deviations						Spatial coherence parameters and component-to-component velocity correlations (Turbulence)									Air density		
	α	β	L_u	L_v	L_w	σ_u	σ_v	σ_w	a_u	a_v	a_w	b_u	b_v	b_w	γ	PC_{uw}	PC_{uv}	PC_{vw}	ρ	
Class	5 m/s																			
N	min	0.1	-15	300	300	300	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	30	650	650	650	0.65	0.65	0.3	5.0	4.0	2.5	0.08	4.5e-3	0.011	0	0.5	6.0	1.0	0.15
S	min	0.2	-15	2	2	2	0.05	0.05	0.05	3.5	4.0	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.2	30	250	250	250	0.495	0.495	0.2	5.0	5.0	2.5	0.08	4.5e-3	0.011	0	0.5	6.0	1.0	0.15
U	min	-1.2	-15	700	700	700	0.655	0.655	0.655	3.5	2.5	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	30	1000	1000	1000	3.0	3.0	2.0	5.0	3.0	3.5	0.08	4.5e-3	0.011	0	0.5	6.0	1.0	0.15
8 m/s																				
N	min	0.1	-15	300	300	300	0.5	0.5	0.5	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	30	650	650	650	0.65	0.65	0.3	7.0	3.0	6.0	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15
S	min	0.2	-15	2	2	2	0.05	0.05	0.05	7.0	4.0	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	1.2	30	250	250	250	0.495	0.495	0.2	11	7.5	6	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15
U	min	-1.2	-15	700	700	700	0.655	0.655	0.655	7	3.0	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	30	1000	1000	1000	3.0	3.0	2.0	11.0	4.0	3.0	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15
11 m/s																				
N	min	0.1	-15	300	300	300	1.1	1.1	1.1	1.5	1.5	2.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.19	30	650	650	650	1.43	1.43	0.75	9.0	3.0	4.0	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15
S	min	0.2	-15	2	2	2	0.11	0.11	0.11	7.0	4.0	3.0	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.6	30	250	250	250	1.09	1.09	0.9	18	12.5	7.5	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15
U	min	-0.1	-15	700	700	700	1.441	1.441	1.441	7	3	2.5	0.0	0	0	0	-3.5	-4.5	-2.7	-0.15
	max	0.09	30	1000	1000	1000	2.5	2.5	1.75	18	5	7.5	0.08	2.5e-3	0.011	0	0.5	6.0	1.0	0.15

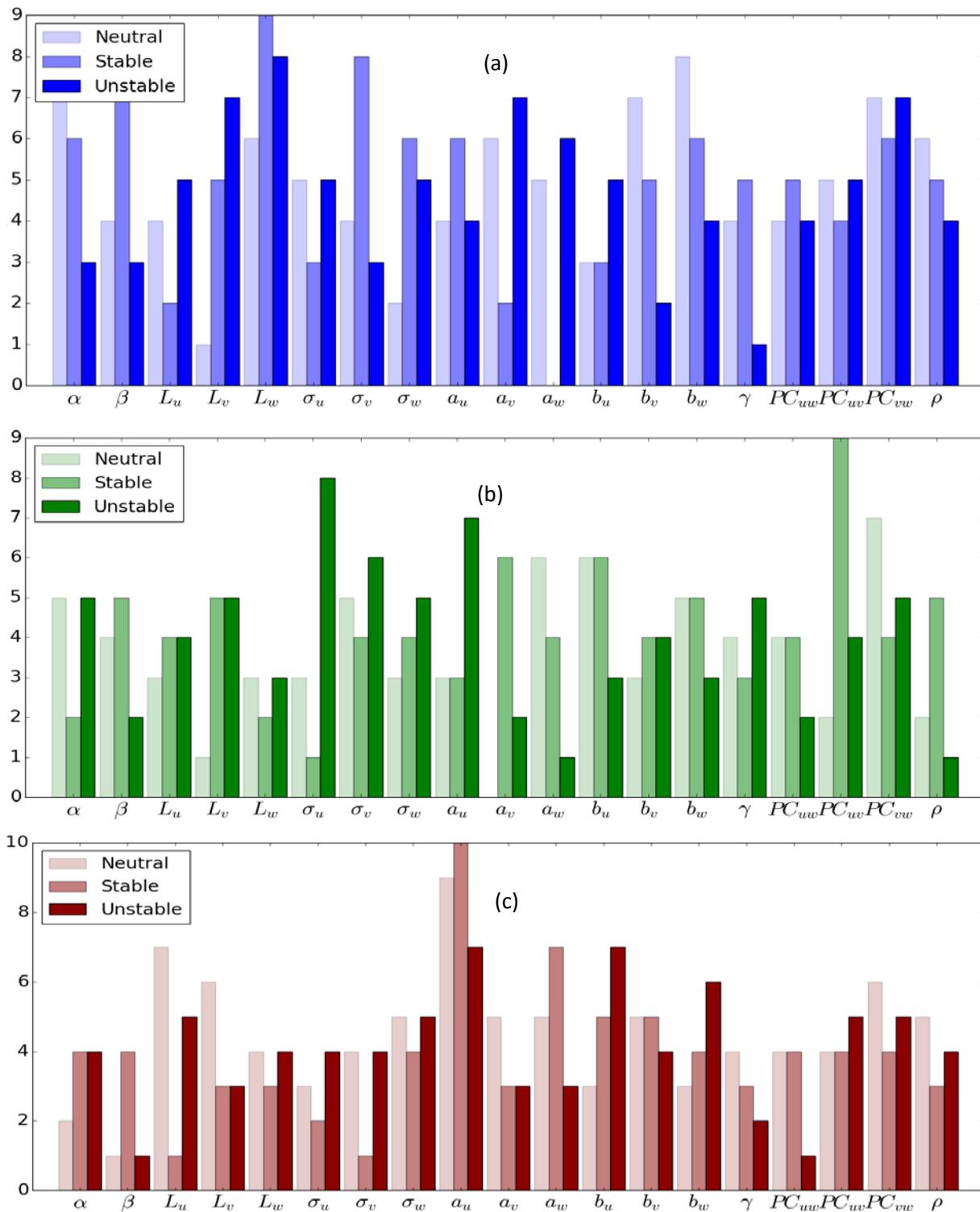


Figure 24. Sensitivity rankings for mean electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3

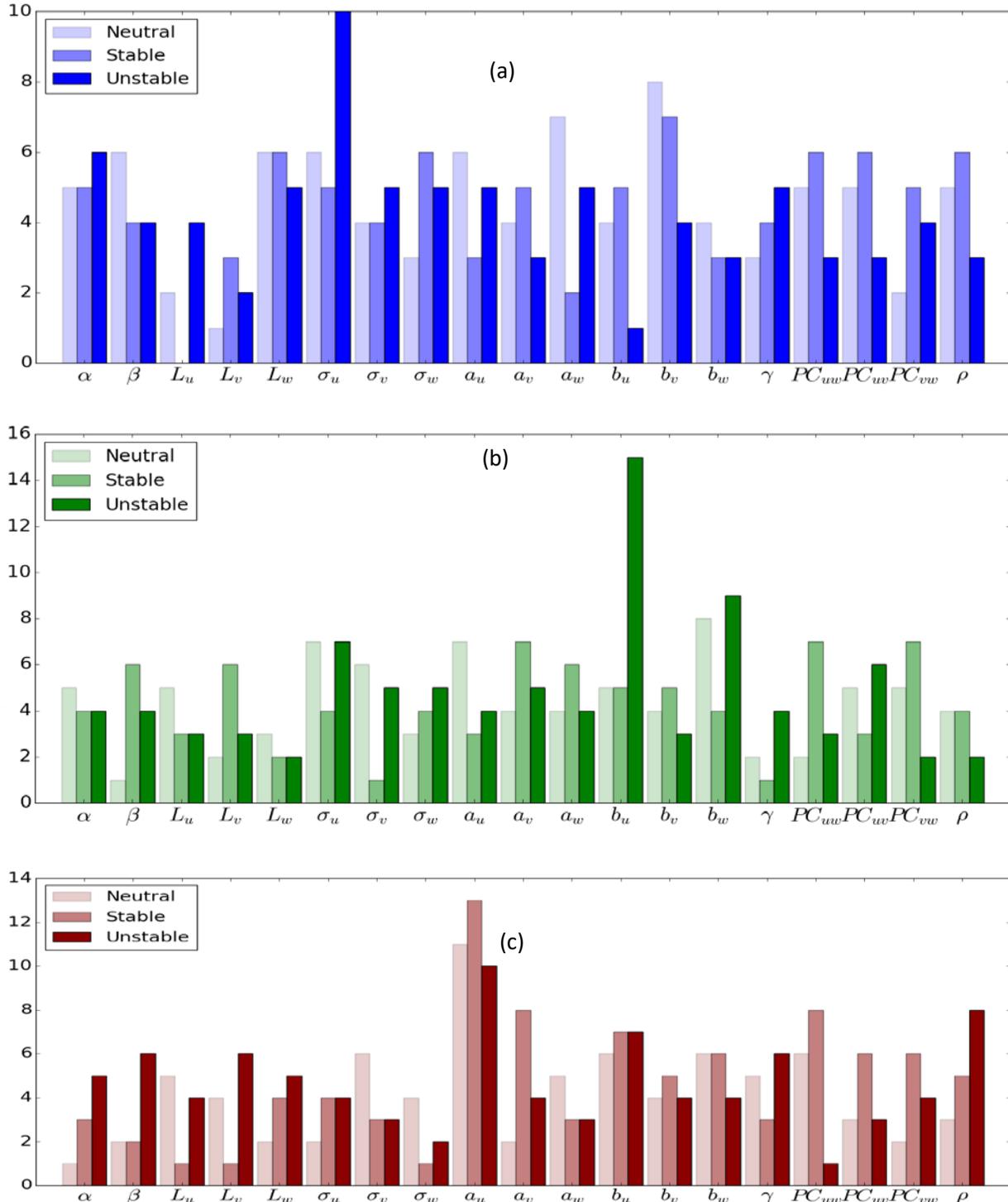


Figure 25. Sensitivity rankings for standard deviation of electric power to different wind parameters (a) Bin 1 (b) Bin 2 (c) Bin 3